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COMPUTER CONTROL OF CHEMICAL PROCESS PLANTS  
WITH SPECIAL REFERENCE TO DISTILLATION

A Thesis submitted for the degree of  
Doctor of Philosophy

by

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Computer Control of Chemical Process Plants with  
Special Reference to Distillation

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SUMMARY

A sieve plate distillation column has been constructed and interfaced to a minicomputer with the necessary instrumentation for dynamic, estimation and control studies with special bearing on low-cost and noise-free instrumentation.

A dynamic simulation of the column with a binary liquid system has been compiled using deterministic models that include fluid dynamics via Brambilla's equation for tray liquid holdup calculations. The simulation predictions have been tested experimentally under steady-state and transient conditions. The simulator's predictions of the tray temperatures have shown reasonably close agreement with the measured values under steady-state conditions and in the face of a step change in the feed rate.

A method of extending linear filtering theory to highly nonlinear systems with very nonlinear measurement functional relationships has been proposed and tested by simulation on binary distillation. The simulation results have proved that the proposed methodology can overcome the typical instability problems associated with the Kalman filters. Three extended Kalman filters have been formulated and tested by simulation. The filters have been used to refine a much simplified model sequentially and to estimate parameters such as the unmeasured feed composition using information from the column simulation. It is first assumed that corrupted tray composition measurements are made available to the filter and then corrupted tray temperature measurements are accessed instead. The simulation results have demonstrated the powerful capability of the Kalman filters to overcome the typical hardware problems associated with the operation of on-line analyzers in relation to distillation dynamics and control by, in effect, replacing them.

A method of implementing estimator-aided feedforward (EAFF) control schemes has been proposed and tested by simulation on binary distillation. The results have shown that the EAFF scheme provides much better control and energy conservation than the conventional feedback temperature control in the face of a sustained step change in the feed rate or multiple changes in the feed rate, composition and temperature.

Further extensions of this work are recommended as regards simulation, estimation and EAFF control.

Key Words

Control, distillation, simulation, estimation, feedforward, interfacing

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Dedicated to Janet

and also

to the memories of a, once fluid, man, crammed  
and distorted by classical mess .....

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# CHAPTER ONE

## INTRODUCTION

## CHAPTER TWO

### LITERATURE REVIEW

Control, Simulation and Filtering

## I.1 REASONS FOR THE STUDY OF DISTILLATION CONTROL

There exist many cogent reasons for interest in the control of distillation columns.

Primarily, distillation columns constitute an important part of many industrial processes - frequently the last separation unit in the process. Therefore, the quality of the product leaving the entire process depends on the quality control of distillation operation. Occasionally, they are vital intermediate units on the constancy of whose products depends the consequential ease of control of succeeding units such as reactors.

Secondly, sufficient available knowledge about the physical nature of distillation enables the creation of reasonably successful static and dynamic mathematical models. The degrees of sophistication of these models are no longer major drawbacks as powerful digital computers can cope with the calculations almost regardless of volume or complexity. Thus, having dispensed with the modelling problems, more attention can then be focused on the control aspects of distillation columns. The implication of this, however, is not that the understanding of distillation as a physical process is complete; outstanding issues such as fluid dynamics and the efficiency of separation on the plates are still not well established and require further research.

Thirdly, the problems encountered in the control of an average continuous distillation column are similar to the typical problems of chemical process control,



the status of which has been the subject of considerable controversy and criticism in recent years.

Finally, the reward for reducing off-specification product in terms of energy saving and economy of operation is, presently, increasing by the day. Although we are living in an ever changing world, it can be confidently asserted that, no matter what the future holds, the cost of production of any commodity will continue to escalate and, therefore, the most effective way to maintain profitability must be to reduce wastage. By the token that energy is the currency of nature regardless of time and distillation may certainly be very wasteful of it, its economical use becomes imperative in relation to distillation.

The literature contains various reports which show that the energy savings of a chemical plant have been enhanced by no less than a half by implementing good control on distillation columns.

The last reason has materialized concurrently with the recent energy crisis and, although more materialistic than academic, can be regarded as the most powerful argument in favour of distillation column control - an incentive that will continue to gain momentum as energy becomes less and less available.

On the other hand, good control of distillation columns by conventional methods is not easy and has been the subject of much research lately. Precise control is difficult to achieve conventionally because:

- (i) columns with many trays exhibit slow response to control action.
- (ii) separation is affected by many variables requiring many control loops that interact with one another.
- (iii) on-line analysis is not always available.
- (iv) distillation units are usually the last in the chain of processing units and are, therefore, subject to changes in throughput from all upstream units.
- (v) the factors affecting separation are not readily interpreted in terms of control system requirements.

In view of these problems, the conventional control methods that will be reviewed later in this dissertation have met with limited success and even a lesser degree of generality on application to distillation columns.

To conclude, it only remains to reiterate that the challenge of distillation column control, although formidable, continues to be extremely attractive.

## I.2 REVIEW OF THE DEVELOPMENTS OF THE CONTROL THEORY AS APPLIED TO DISTILLATION

Up until the early sixties there was no standard method of controlling distillation columns and no system had been found capable of forcing a column to behave as the designer had intended. But then a revolution began and, for the past two decades, various groups working independently have been apparently making strides in the areas of the dynamics and control of distillation columns.

Although the published work is extremely diversified, broadly speaking, three distinct paths can be identified in the developments made in these areas which are namely:

1. The deductive path
2. The mathematical path
3. The computer path

Admittedly, the computer and the mathematical paths do overlap to some extent in that they are in effect complementary. Nonetheless, they will be treated separately in order to contrast and better elucidate them. The computer path would perhaps be better worded as a mathematical path to which the computer is an indispensable tool. Completion of any control configuration in any process control practice comprises two stages:

1. The analysis of the control problem which includes detailed study of the dynamics of the process under consideration.
2. The synthesis of the control strategy including

stability studies. ~~ables which are then treated as~~

Computers can be an important tool in both stages.

In this capacity, they have affected the development of control theory in the following ways:

1. They have enabled complicated solutions to be synthesized by the use of computer aided design techniques.
2. They have enabled complicated control configurations to be implemented.

Additionally, there has also been some development of ideas through experimentation but this has been limited because the verification of control strategies by experimentation is usually only valid for the specific cases under consideration.

The deductive path, as reflected in the work of Shinskey and co-workers (17,18,31,32) by-passes the first stage and avoids the problem of dynamics completely and is purely based on observations and experience. It is characterised by the logical arrangement of arguments and observations to detect regularities of behaviour without too much recourse to formulae.

The concept of material balance control which appears to be the most industrially acceptable control method falls into this category. It is essentially a system designed to hold the process in dynamic equilibrium - notwithstanding variations in throughput and environmental conditions - by reducing the interaction between the column's heat and material balances. Further, heuristics are introduced for coupling the manipulated

and the controlled variables which are then treated as single-loop systems and analysed by classical control theory. The resulting control scheme is then implemented by conventional hardware.

On the one hand, classical control theory suffers from the inability to handle non-linearities and to guide the control system design for a dynamically interacting multivariable process such as distillation. On the other hand, the literature contains no evidence as to how far-reaching these rules of thumb may be. Therefore, the scepticism about such a simplistic approach may not be totally unjustified. The margin between sophistication and sophistry is always narrow in deduction and inference and there can be few subjects where the risk of developing into an armchair philosopher is greater than it is in distillation dynamics and control.

The followers of the mathematical path, however, have approached the problem more realistically and with inspired thought inasmuch as they have acknowledged the multivariable nature of the distillation control problem. Modal control proposed by Rosenbrock (33) and various attempts to apply feedback and feedforward control belong to this class, all of which are direct translations of control techniques employed elsewhere except modal control which has an air of novelty around it. An excellent exposition of modal analysis and some useful examples are given by Gould (23). These techniques will be reviewed in more detail in Chapter II.

The main feature of the mathematical path is the

fact that it is essentially concerned with deriving equations to describe an individual stage in the reported Laplace or time domains and stepping this up from a single stage to a column with a number of similar stages. The dynamics are then studied and control configurations are specified by solving the control problem analytically or numerically. For example, in application of optimal feedback control to a binary distillation column the matrix Ricatti equation as used by Jordan (25) had an analytical solution proposed by Walter (26).

It is also of interest to note that in contrast to the deductive path that aims at minimising interaction, the mathematical path usually advocates the exploitation of interactions as in the case of modal control.

The amount of detail that should be included in these mathematical models to make them realistic representations of the phenomena occurring in distillation columns is, nevertheless, not clear-cut and yet another major shortcoming of the mathematical path is due to its inability to guard against the practical problems of the implementation of the derived control strategies. These problems are highlighted in unknown disturbances, non-linearities, inherent measurement errors, lack of availability and infrequency of primary control measurements.

Despite the upsurge of enthusiasm for the mathematical path that followed the introduction of modal



control by Rosenbrock (33), the interest in this path appears to have subsided and very few cases are reported in the literature that are indicative of any potential progress in the application of such techniques to distillation control. To some extent, this is the reason why control practitioners are rarely interested in the mathematical path - especially in the industry.

This lack of progress, however, is thought to be partly due to the inherent amount of calculation involved in such approaches which in many cases may prove to be prohibitive particularly in multicomponent distillation. Yet another obstacle has been the practical problems of implementation of the consequential control strategies. For instance, for this very reason any successful demonstrations that multivariable control can, indeed, achieve superior results to the conventional single-loop approach may have been hampered.

In other words, although the theory is good, it has failed to achieve the deserved results in practice for the reasons mentioned above.

The advocates of the computer path have, however, shown more signs of life. A few workers such as Brosilow and Weber (34), encouraged by the increasing availability of computers especially for on-line prediction of dynamics and control, have made better use of them to study more realistic situations. They have faced facts concerning model inaccuracies, unknown disturbances and the scarcity of reliable primary measurements : and to overcome these problems, they have

proposed the use of various optimal or sub-optimal static or dynamic estimators.

More recently, the on-line use of digital computers for data acquisition and control has been advanced. With the increasing availability of high speed digital computers and the advent of micro-processors, they should continue to consolidate their position as an accepted tool of the trade.

### I.3 THE ROLE OF THE COMPUTER

In a retrospect of the past two decades of distillation column control the conclusion is inescapable that any approach to control that does not include the prediction of the dynamic behaviour of the column will not suffice. The prediction of the dynamics of a complex process of a high dimensionality such as distillation cannot be accomplished effectively without a computer since the sheer volume of calculations needed for even a small column makes it humanly impossible to cope with.

On the control front, for example, using optimal control theory to develop a controller would involve a feedback matrix relating the state vector to the vector of the manipulated variables. Needless to say the ease of implementation of such a system on a computer is more attractive than implementation by hardware. Further, this matrix may even be time variant which would confuse the issue even more when conventional hardware is used. Not only may the computer be cheaper, but it would almost certainly be easier to implement.

Continuing in this context, the computer can greatly assist the examination of the past record to find the best conditions in which the process should run, particularly when different shifts operate a column in different fashions - the computers are not solely controllers and may act as data-loggers which produce information that may be of use for more productive use

of the column.

It is to be that extensive research

In the previous section, it was stated that precise control is, in practice, marred by noisy or corrupt measurements. The only way to refine these measurements, and thereby improve control, is by stochastic estimation methods - whether they be primary or secondary measurements - and this is not a difficult task for an on-line computer. Indeed, in this capacity, the role of the computer as an aid to control can hardly be equalled.

Sadly, while computers have become widely accepted as control aids in industries such as the steel industry, they do not appear to have achieved the same level of recognition in the chemical industry. But at long last this picture has begun to change over the past five years with the dramatic decrease in the cost of computers that has eliminated the economic deterrent against their use. The other major obstacle, however, lies in the fact that, in chemical industries, there are frequently fire hazards which necessitate the use of non-electrical or heavily-proofed electrical measurement and valve systems. Digital computers require electrical inputs and this means that either pneumatic-electric convertors or heavily proofed electrical systems must be utilized. A large part of the problem in interfacing computers to chemical processes is due to the fact that the electrical signals to the actuators on the plant and from measurement devices may have to satisfy stringent demands which are costly

to comply with. It might be that extensive research into interfacing chemical plants to computers would produce a significant drop in the cost of on-line computers.

To sum up, despite the remaining problems of interfacing that should be removed in time, the increasing complexity of chemical process industries and the speed at which decisions need to be made should promote the extensive use of high speed digital computers to help the engineers in the estimation and control of the states of the systems.

#### I.4 THE ROLE OF SIMULATION

Yet another impetus for the use of high speed digital computers as an aid to design and control of chemical processes stems from the growing tendency towards a more quantitative approach to problems of design and control, inasmuch as powerful computers can be of great value in solving complex systems of mathematical equations statically or dynamically - equations that would have been impossible to solve analytically.

Generally speaking, as regards distillation columns, or any process plant, simulation can be subservient to engineers in the following ways:

- (i) alternative designs can be sought to achieve more efficient and optimal operation of existing plants
- (ii) dynamic and static characteristics of future plants can be predicted and optimized
- (iii) the computerized analytical approach provides a deeper understanding of the internal mechanisms of the processes studied
- (iv) different control schemes can be tried rapidly and economically on a simulation instead of the alternative time-consuming tests on the actual or pilot plants

All these factors, viewed collectively, culminate in describing simulation as an effective technique of improving the profitability of an existing or proposed



design.

In a world ever conscious of costs and profits, every technique which helps to improve efficiency must be considered; simulation provides some of the important methods for achieving these objectives.

The pioneering works of Franks (2), Ramirez (5), Luyben (3) and Robinson (4) have gone a long way to introduce and establish this important tool for chemical engineering practice. The work of Kocak (36) on dynamic simulation of chemical plants is another example of the growing interest in this area. No doubt interactive simulation should follow suit and extend the flexibility and the horizons of the process simulation even further to make it more fascinating.

In relation to this thesis, simulation has been used to serve the following purposes:

1. To study the dynamic behaviour of a binary distillation column.
2. To explore the possible functions to be fulfilled by the Kalman filter.
3. To test control configurations prior to implementation on the column.

## I.5 THE ROLE OF ESTIMATION

Control is mainly concerned with decision making and therefore taking action to counteract any undesirable disturbance that might have an adverse effect on the state of a physical system.

Pre-requisite to making timely and expedient decisions are the availability of reliable information about the system, the nature of the disturbances and the way in which these disturbances are manifested in the system - i.e. the response of the system.

As regards chemical processes, in the face of a disturbance, one might wait for the effect to manifest itself in the system, measure the magnitude of the effect and then take appropriate corrective action, which is commonly known as feedback control. Alternatively, one could choose to anticipate the effect of the disturbance by a mathematical description of the physical system and, in theory, nullify the effect before it materializes - in other words feedforward control.

Occasionally a combination of these two techniques is used to increase the chances of success in controlling the state of the system. Whatever the philosophy of control may be, two sources of information are available to the engineer; these are, namely, the measurements of the process variables and a mathematical description of the physical system based on physico-chemical laws. In chemical engineering systems these are both subject to errors.

To succeed in controlling a system, some information about the state of the system is necessary. In fact, mathematical descriptions and measurements may be regarded as being the tools of acquiring such information. In a real chemical engineering system which is subject to disturbances there is a true state which will never be known exactly and a few variables which can be measured only inaccurately because of noises in the measurement instruments and in the communication channels. Invariably, the mathematical description of the system is also inaccurate.

The problem of accurately determining the state of a system from noisy measurement is called estimation or filtering. It essentially involves recovering reliable information from corrupt measurements and, optionally, combining the recovered information with the predictions of a mathematical model to provide the "best" estimates of the state of the system (e.g. Kalman filtering). In 1960, Kalman (35) extended the filtering theory to cover the estimation of the states described by a set of linear differential equations and following this development, the classical Kalman filter has been applied in many diverse fields, in particular in the aerospace industry. More recently, the extended version of the Kalman filter has been proposed to deal with non-linear systems.

The following broad classes of problems require estimation techniques:

- (i) the determination of model parameters in non-linear algebraic models from experimental measurements.
- (ii) the off-line determination of model states in non-linear dynamic models from time-sampled experiments.
- (iii) the on-line modelling of dynamic processes where sampled output signals are used to generate estimates of the states and parameters in process models.

The techniques involved in the second and third classes of problems are classified as non-sequential or sequential estimation. In the sequential approach estimates of state variables and parameters are generated at each sampling instant. The non-sequential approach is based on taking a series of samples over a period of time.

A sequential approach to estimation is commonly referred to as recursive filtering because current state and parameter estimates are calculated as the output measurements become available; hence one is continuously filtering the system. The recursive filtering problem can thus be identified as the estimation of the current states of a dynamic system using all the past and present measurements without the necessity of storing the past measurements.

Another significant application of estimation in chemical engineering is in relation to control and emerges in the form of estimating product quality from secondary process measurements. For instance, in

distillation columns a corrupt temperature measurement may be used to estimate the composition on a plate where equilibrium conditions may not necessarily be prevailing - i.e. the filter functions as an on-line analyzer.

As far as estimation is concerned, its application in off-line and on-line modes are investigated in this research. In an off-line capacity, an extended Kalman filter is used to sequentially refine an inaccurate model and estimate parameters such as feed rate and feed composition using information from the column simulation which is known to be reasonably accurate. It is first assumed that compositions are available directly and then plate temperature measurements are accessed instead. In an on-line mode, the role of the estimator is much the same as the off-line case except that the column simulation can be replaced by the actual column and a mini-computer can be employed for real-time data acquisition, estimation and control.

## I.6 THE ROLE OF FEEDFORWARD CONTROL

Without loss of generality, one can say that the feedback control method has been the traditional method of controlling distillation columns in the industry. It often provides acceptable control despite scant knowledge of the dynamic character of the column. However, corrective action is taken only after the product qualities have deviated from their desired values, and long times are often required to bring the unit back to the desired steady state, especially in large towers. This can be considered as being a defensive attitude.

We live in an era in which economic constraints are making survival increasingly difficult in any area. Therefore, common sense dictates that we cannot afford the expensive luxury of waiting for things to go wrong before taking any counter measures. A deviation in product quality, when it occurs, is already costly. Indeed, man has much to gain in the game of economic survival by anticipating the adversities and taking counter measures before his system is disturbed. Feedforward control is compatible with this school of thought. It is heartening to know that this fact has been acknowledged in chemical process industries in the past decade and feedforward control systems have gained wide acceptance in chemical engineering systems. They have demonstrated their ability to improve control, sometimes quite spectacularly (Luyben (3)). It is indubitably a



control philosophy that is more relevant to chemical engineering systems than any other engineering fields. Our systems are often slow-moving, multivariable and contain appreciable dead times. All these characteristics can make life awkward for feedback controllers whereas feedforward controllers can handle them with relative ease.

The basic notion of feedforward control is to detect the disturbances as they enter the process and make adjustments in the manipulated variables so that the output variables are held constant. One does not wait until the disturbance has worked its way through the process and disturbed everything to produce an error signal. If a disturbance can be detected as it enters the process, it makes sense to take immediate action in order to compensate for its effect on the process.

In application to chemical processes, feedforward control usually suffers from the following limitations:

1. Inexact mathematical or empirical models are used to predict the dynamic behaviour.
2. Changes in controlled variables caused by unknown or unmeasured disturbances may go uncorrected.

It is argued in this thesis that the dyad of a Kalman filter and feedforward control scheme should overcome these problems.

## I.7 THE OBJECTIVES OF THIS THESIS

This thesis is concerned with a research project whose prime objective is to carry out investigations into the computer control of chemical process plants with special reference to the control of distillation columns. It essentially comprises the following stages:

- (i) the construction of a distillation column with the necessary instrumentation and its interfacing to the Honeywell-316 computer with special bearing on cheap and reliable methods of level, flow and temperature measurements that are sufficiently accurate and immune from noise.
- (ii) the dynamic simulation of binary distillation columns employing a model that incorporates fluid dynamics in a realistic and easy-to-handle fashion in the form of plate liquid holdup calculations.
- (iii) the exploration of the dynamics of the distillation column and comparison of experimental results with the predictions of the simulation.
- (iv) application of an extended Kalman filter to the column simulation in an effort to demonstrate the use of Kalman filter for model refinement.
- (v) estimation of tray compositions from secondary measurements such as flowrates and temperatures by a Kalman filter by simulation.

PROCESS CONTROL  
(vi) feedforward control of the distillation column  
using a Kalman filter followed by the comparison  
of results obtained with those of a conventional  
control method by simulation.

## II.1 THE STATUS OF CHEMICAL PROCESS CONTROL

The status of chemical process control has been the subject of intense controversy in recent years. We are now two decades into the era of modern control theory and many theorists, pointing to the apparent advanced applications in the aerospace industry, wonder at the tardy pace of application in the process industry.

Control practitioners conventionally argue that modern control theory is not relevant to the chemical process control and that classical techniques and designer experience will always lead to satisfactory and perhaps optimal solutions. Publications by these groups have done little to establish a satisfactory dialogue; few practitioners appear to have more than a superficial knowledge of modern control theory; modern control researchers have produced few convincing examples of successful chemical process applications (Wooyoung and Weekman (37)).

Further, the techniques of chemical process control, although superficially in good health, are in many important respects at a point of conceptual stagnation. Even the splendour of digital computers which are now shepherding many chemical processes, cannot hide the pervading thinness of substance in their assigned tasks.

A brief review of the two available control theories for chemical processes, namely the classical and the modern control theories, at this stage, may not go amiss. The outstanding features of the classical

approach are as follows:

- (i) a linear model of the system is assumed, and the designer then proceeds to describe the system in terms of transfer functions of either frequency or Laplace variety depending on the type of information available to him
- (ii) an almost exclusive emphasis is placed upon specific control systems classified as the servo-mechanisms
- (iii) mostly single-input-single-output systems are considered
- (iv) it usually draws on the indirect design techniques of the trial-and-error type.

Thus, the classical approach does enjoy the following important and time-tested advantages:

- (i) no sophisticated mathematics are required beyond the elements of linear differential equations and complex algebra
- (ii) it utilizes a linear model which in the great majority of cases is found to be quite adequate in its representation of the important poles, zeroes and delays at the nominal conditions of operation.

Nonetheless, it also suffers from the following disadvantages:

- (i) empiricism which may entail lack of generality
- (ii) trial-and-error design that may be time consuming
- (iii) restriction to single-input-single-output systems only.

Moreover, while acknowledging the usefulness of this classical approach for single-loop systems, some also criticise it for not yielding an optimal control and for its inability to handle non-linearities. These criticisms fade to insignificance when one discovers its total inability to guide the control system design for interacting multivariable processes. The control of both top and bottom compositions of a distillation column is an oft-cited example of control difficulties in interacting chemical processes. While the classical control theory is capable of analysing the difficulty, it has nothing to suggest as a remedy. The seat of its impotence is in its reliance on the designer to specify the control configuration.

The control technique normally employed for chemical plant systems is indeed, much in line with the classical theory inasmuch as it essentially involves choosing a set of measurable variables which when controlled at some value are expected to enforce the quality, throughput and safety requirements of the plant. As far as possible, these variables are then controlled with a collection of single-loop controllers, manipulating easy-to-adjust variables - usually flowrates. Modifications to single-loop concept such as cascade, feedforward, ratio, non-linear elements etc. are then made as they appear necessary. During the start-up of the plant, the mode adjustments in the feedback controllers are adjusted largely by trial and error to achieve adequate performance. Needless to say, this approach draws



heavily on past experience or on pilot-plant control systems.

The single-loop approach has many advantages for the operator, for maintenance personnel and the reliability of the operating unit. It is handily analysed by linear design technique. The rationale of the theory and the methods of application to chemical processes are clearly and succinctly presented by Gould (23). The use of a linear model on inherently non-linear processes is not a restriction of significant consequence in the great majority of cases and this indubitably provides further incentive for the use of this classical technique. Yet another point that can be brought up in favour of single-loop control is the fact that it often facilitates detection of any of a vast number of possible failures in minimum time and hence speedy corrective action becomes possible.

In spite of their many advantages, as stated before, single-loop controls will not always provide adequate control and thus must be improved upon. The most difficult task for the design engineer is to determine first those cases where a simple control system is not sufficient and then to devise an adequate solution using a control system which is as simple as possible.

In view of the inadequacies of single-loop methods in the treatment of dynamically interacting processes, one might be tempted to turn to the theory of non-interacting control (Gould (23)). In this technique a design is sought such that a change in the set point of

one variable affects that variable only. This is achieved by choice of a control matrix such that its product with the process transfer function is diagonal. With diagonalization achieved, the various consequential control loops are then non-interacting and single-loop control theory may be used to design each loop separately. Foss (38), after a review of the shortcomings of this approach, suggests that non-interacting control is not worthy of consideration for process control. According to him, these interactions should be exploited rather than avoided and needless to say exploitation of interaction in multivariable processes "takes brains, judgement and maturity" - not to mention a good theory which remains elusive. Modal control proposed by Rosenbrack (33), is a technique that exploits these interactions to achieve control objectives. This technique will be discussed in more detail at a later stage in this thesis.

The allusion to modal control leads us on to the other approach to chemical process control, namely, modern control theory which encompasses such control techniques as modal control, optimal feedback control, optimal feedforward control, and model reference adaptive control.

It essentially possesses the following features:

- (i) it approaches the problem in a more fundamental fashion. For example, it defines the concept of control and establishes test procedures for determining when and under what conditions a system is controllable. Direct synthesis methods

are proposed which lead to unique system designs that are optimal in some defined sense.

- (ii) extensive use is made of a computer for analysis of the control problem, synthesis and sometimes for the implementation of the control solutions.
- (iii) it does not limit itself to linear models. Therefore, time-domain system descriptions (state-space approach) are preferred to transfer function methods.
- (iv) it draws heavily on more advanced mathematics such as calculus of variations and matrix algebra.

Modal control is a novel approach to the analysis and design of control systems for very complex processes. In theory, this method can be used not just to determine the settings of the controllers but also can serve as a systematic guide for selecting control system configuration. The approach is based on the notion that the dynamic behaviour of a system can be represented by the motion of a point in an  $n$ -dimensional space (state-space) which leads to a mathematical model in the form of  $n$  first order differential equations. The theory essentially centres around the theme that the transient behaviour of a process is predominantly determined by the modes associated with the smallest eigen values. It is, therefore, proposed that the rate of response of these modes be increased to an acceptable level by positioning the mapping of the input control vector in the subspace spanned by the eigen vectors of the controlled system. When this can be accomplished and when

the activation of the modes can be measured, the eigen values or the time constants of the closed loop process can be adjusted independently through a proportional feedback control matrix. In principle very rapid and stable recovery can be achieved. Modal control is thus a technique that exploits interactions among variables to achieve control objectives. However, Foss (38) indicates that, unfortunately, but not unexpectedly, such ideal circumstances do not obtain in chemical process systems. The ability to measure only a very few of the states may lead to inaccurate estimates of modal activations, and the handful of process inputs in general cannot be aligned with process modes. Both these facts of life can, indeed, cause serious deficiencies in control systems designed by the modal techniques. Nevertheless, attempts have been made to apply the idea to the control of diffusive distributed processes, a distillation column, a boiler, and a 41-variable chemical plant model (23, 42, 43). In these investigations knowledge of the modal character of the process was used to suggest the choice of measured and manipulated variables, i.e. the control configuration.

While there remain potentially useful developments of modal control to assist in the determination of control system configuration, Macfarlane (44) points out that there exist several disadvantages to this idea. Primarily, the method gives attention only to the poles of the system; closed-loop zeroes, which could also influence the system behaviour are left unattended.

Further, the method does not address the regulation of specific output variables.

The theory of optimal control, by its very name, would seem to promise a best compromise among all the conflicting requirements of process control systems. But it does not. Rosenbrock and McMorron (109) indicate that "The word optimal carries with it the suggestion that the system has desirable properties in general, but of course, this need not be the case". There are, indeed, many undesirable properties and unworkable features of the theory as it has been developed for chemical processes.

Optimal control, defined in various ways, has been attempted of stirred tank reactors, tubular processes, distillation columns, extraction columns etc. Objectives in these attempts have been to determine (open-loop) manipulatable input histories that minimize the time required to bring the process to a new state or the (closed-loop) feedback and feedforward gains that minimize a quadratic functional of the process states and control inputs. Other objectives such as maximization of reaction yields have also been attempted.

Upper and lower bounds on the control input are imposed in the time-optimal case with the result that the optimal inputs may reside at one or the other bound for all or part of time (so-called bang-bang control). The switch from one bound to another is determined by switching curves that are calculated from the necessary conditions for minimum time, a calculation involving the integration of the state and adjoint differential

equations with split boundary conditions. The calculations are difficult and lengthy. In all this, of course, one assumes perfect knowledge of the process model and parameters and that there are no process disturbances.

Foss (38) goes on to say that in view of the unlikely attainment of these assumptions and the infrequency of purposeful state changes, startups and shutdowns in continuous processes, it is difficult to appreciate the utility of such a theory for the control of chemical processes.

Various attempts have been made to develop algorithms for the computation of this type of control which can be very difficult to understand. Perhaps the usefulness of such a theory can be argued in some special cases but, in the light of the circumstances encountered in chemical processes, its quantitative value is slim for the processes and situations so far treated in the chemical engineering literature.

Optimal feedback control, viewed with respect to applications to chemical processes treated so far appears to be no less immune from criticism. A review of the reasons as to why optimal feedback control is also open to such powerful criticisms has been given in the aforementioned paper by Foss.

Therefore, it appears rational to finish by saying that investigation into requirements for good process control is imperative. It has been argued here that problems, needs and objectives of process control differ so significantly from those in other fields that



the nearly direct translations of methods developed elsewhere have little practical values for process control. We must always remember that our systems are non-linear, usually slow-moving, contain appreciable dead times and are subject to unknown disturbances. These problems are further compounded by the fact that our mathematical models are usually inaccurate, the system parameters are normally uncertain and primary process variables are very often difficult to measure.

## II.2 CONTROL OF DISTILLATION COLUMNS : THE LITERATURE

### REVIEW

The literature abounds with applications of various methods for control of distillation columns. The objective here is to review these methods and, where need be, concisely expound their theoretical concepts in an effort to explain how they relate to the classifications introduced in Chapter I. Attempt is also made to highlight the relevance and the possible use of an estimator in relation to those methods where appropriate. The model-independent feedback methods essentially constitute the deductive approach while the model-dependent methods such as feedforward and modal form the mathematical path to the control of distillation columns.

### II.2.1 THE DEDUCTIVE APPROACH : MODEL-INDEPENDENT FEEDBACK CONTROL METHODS

Model-independent feedback forms of control have been the traditional methods of controlling distillation columns and have often provided acceptable control despite scant knowledge of the dynamic character of the column. The deductive path, referred to in Chapter I, is essentially constituted by the feedback forms of control in which attempts are usually made to reduce interaction in the column without recourse to a mathematical model and using conventional hardware. At the risk of being tautological, one must restate that the guidelines followed in the deductive path have been past experience, inference and empirical structures and, indeed, this fact is echoed in the forms of control that will be discussed in this section. In control language, the deductive path differs from the mathematical path in two different ways. Primarily it avoids the problem of the dynamics and secondly, the synthesis stage is normally accomplished by single-input-single-output (SISO) methods or, more often by on-line tuning.

The following forms of control that have appeared in the literature are basically deductive:

- (i) single-plate temperature control
- (ii) multiple-plate temperature control
- (iii) material balance control

### II.2.1-1 Single-Plate Temperature Control

On-line control of distillation columns requires that a measurement should be made of the composition of the product or of some variable which is indicative of the product composition. The most common measurement used for product quality control is a tray temperature near the end of the column from which the product comes. The location of the tray for temperature measurement is very important. It should ideally be at a tray which exhibits a reasonable temperature variation when product quality changes, yet be near the end of the column producing the product whose purity is being controlled. A large number of workers have suggested that product quality should be controlled at both ends, yet a lot of columns are still solely controlled at one end. This is by virtue of the effectiveness of separation in one half of a column which negates the necessity for control loop in that half owing to the over design of the columns. Therefore, single-plate temperature control simply means a control based on a single temperature measurement in either the enriching or the stripping sections.

The most usual single-plate temperature control scheme is depicted in Figure II.2.1. Here, the reflux drum and reboiler levels are controlled by the product off-take rates. The product quality at either end - as assessed by the temperature measurements near the ends of the column - is controlled by the amount of recycle to each end of the column.

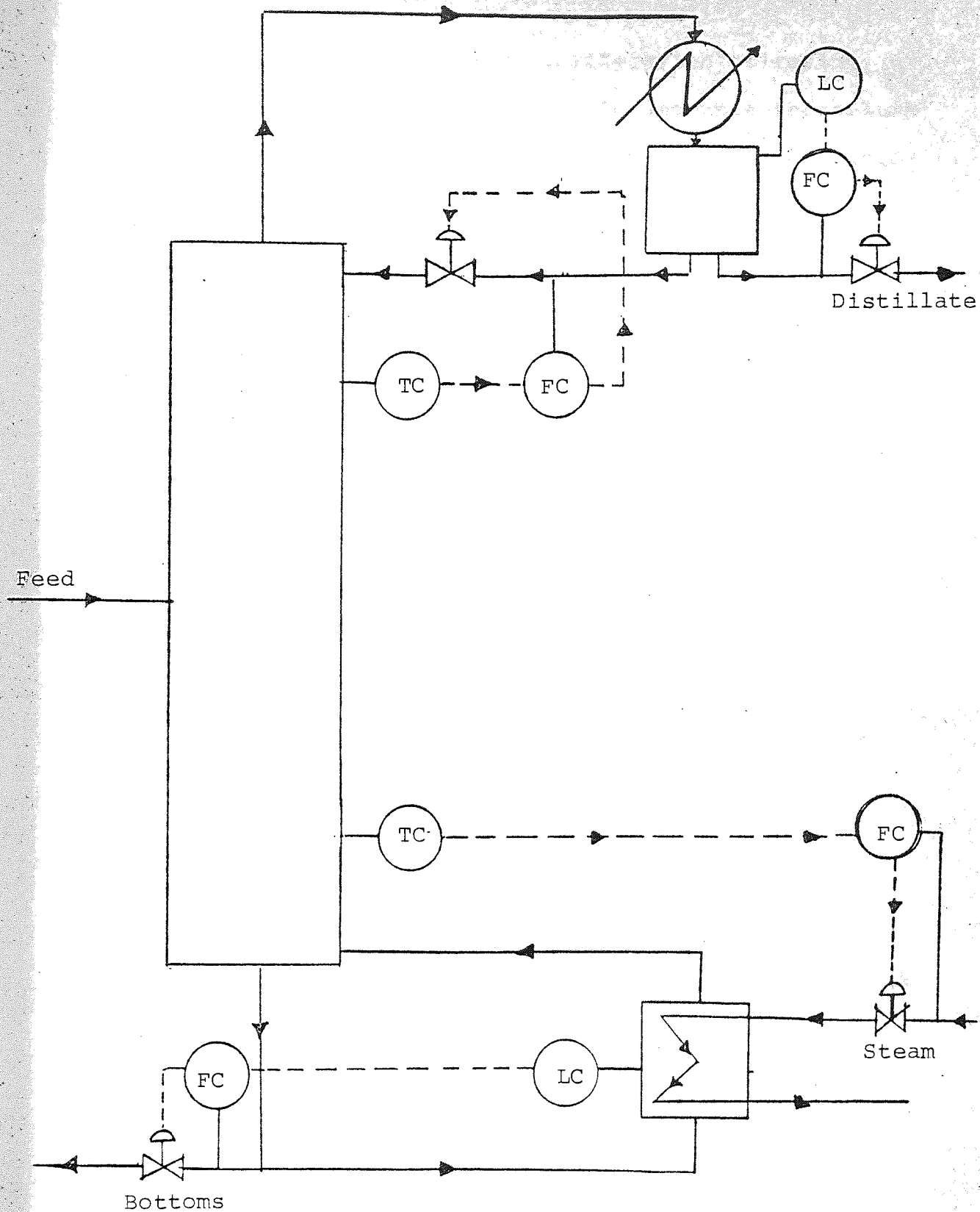


Figure II.2.1. The Standard Control Scheme for Distillation Columns.

Based on McCabe-Thiele consideration of reflux ratio and in an attempt to start to decouple the column, some workers (45,46) have introduced the idea of ratio-ratio control. In this approach, the hold-up tank levels are controlled by the product off-take rates and the ratio between the recycle rate and the product off-take rate at either end is controlled by a temperature measurement near the ends of the column.

Jordan (25) points out that it is of paramount importance to note that these methods satisfy the steady state requirements of the column but not necessarily the dynamic requirements of the control system. Moreover, the attempt to decouple a physical system appears to be unrealistic.

These workers have also suggested that for more accuracy, measurement of pressure near the temperature measurement point is requisite. Normally, a simple temperature measurement of the boiling point is used to assess the composition but in presence of pressure variations this practice becomes inaccurate. Therefore, the pressure in conjunction with temperature may give a better approximation to the composition on the plate. The schematic diagram of a ratio-ratio control structure using pressure-corrected temperatures is given in Figure II.2.2.

It is suggested that ratio-ratio control can readily cope with situations where levels initially change faster than temperatures.

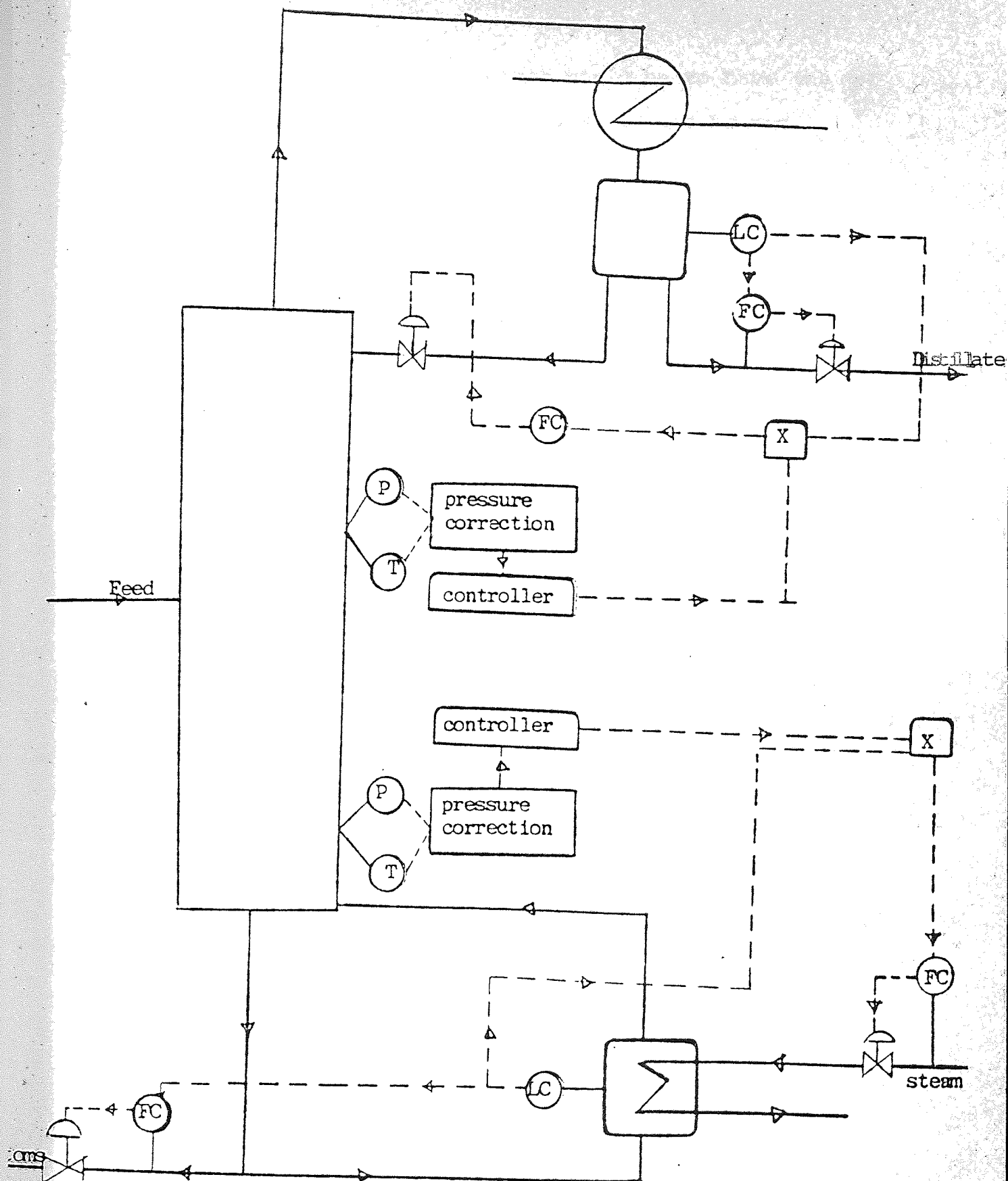


Figure II.2.2

The control structure for ratio/ratio control using  
pressure corrected temperatures



Another possible structure would be to have the levels control the product rates while the bottom temperature trims the ratio between the reflux and the steam rate as illustrated in Figure II.2.3.

This control structure is problematical owing to the fact that the trimming of the control loop is highly critical. If the bottoms level starts to drop due to a reduction in the feed rate, the bottom level controller will reduce the bottoms rate and due to the ratio between steam and the bottoms rate, the steam rate drops off, and this, in turn, leads to a reduction in the reflux rate due to the second ratio unit. The reduction in the reflux rate means a lower liquid rate into the bottom holdup and, therefore, this leads to a further cutback in the bottoms rate. In other words the system is undesirably at minimum phase. Comparative results using this kind of structure to control a column subject to feed changes have been unimpressive.

A variety of such schemes have been proposed by Perry (1), Gould (23) and Shinskey (18) to deal with various situations encountered in practice.

Rosenbrock (47) suggests that interaction can be further reduced by controlling  $(x_1+x_2)$  with the reflux and  $(x_1-x_2)$  with the reboil :  $x_1$  and  $x_2$  stand for the composition measurements at either end which are normally inferred from temperature measurements.

It is of interest to note that Rosenbrock's proposal is embodied in an appendix to his paper and in fact, later in the same year, he propounded the notion of

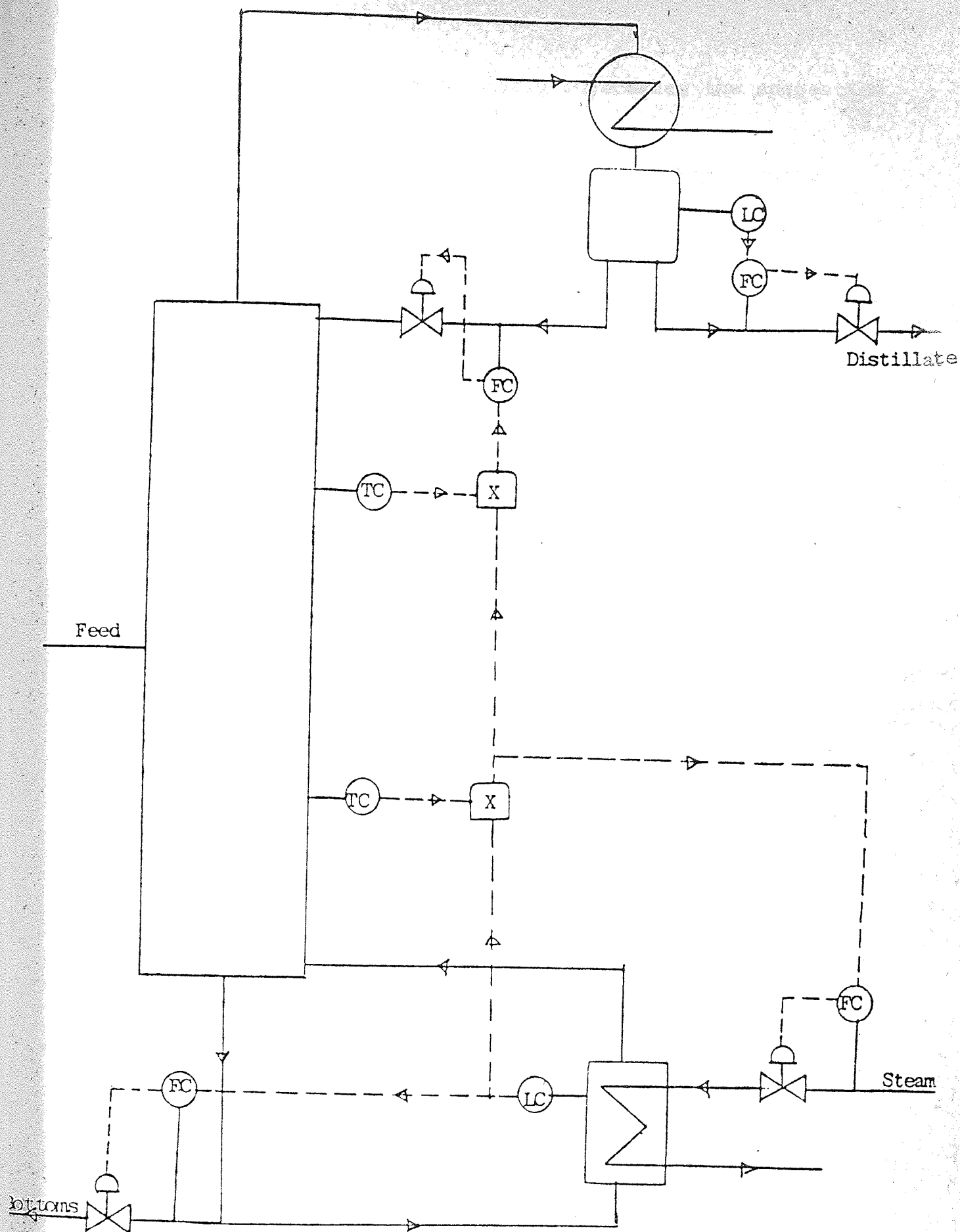


Figure II.2.3

A control structure which attempts to allow for internal interaction between reboil and reflux.

modal control which effectively supersedes the suggestion mentioned above.

It goes without saying that in all these control exercises, the proper tray location for temperature measurement is of utmost importance. The proper tray can often be determined by measuring the temperature profile of the column experimentally. A typical distillation column temperature profile is depicted in Figure II.2.4.

#### II.2.1-2 Multiple-Plate Temperature Control

In an attempt to improve control, some authors (45, 46) have suggested pressure corrected temperature measurements while others have proposed the use of several temperature readings.

As an example, one could, at the outset, mention the work of Weber (48) who measured the temperature difference between two points in a section of the column to control it. The sole advantage of this approach is reflected in the fact that both temperatures are affected by pressure changes in the column and because the difference is used, the effect of pressure on the boiling point can be neglected.

Luybon (49) used a double-differential temperature as the input to the controller. This is best elucidated in Figure II.2.5. Here the controller input is  $(B_2 - B_1) - (B_3 - B_2)$  or  $2B_2 - (B_1 + B_3)$  where:

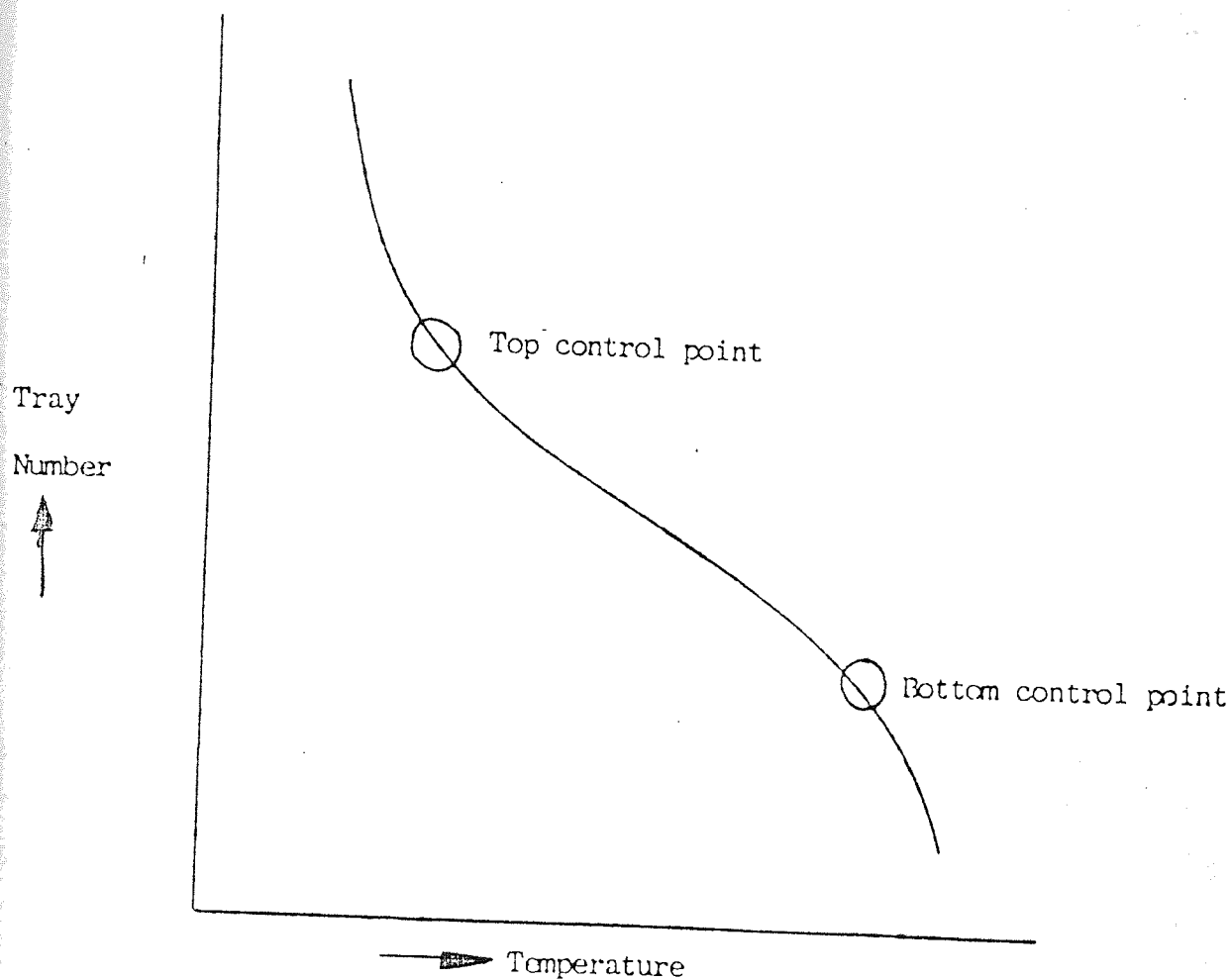


Figure II.2.4. Column temperature profile with typical temperature-control-measurement location for binary mixtures

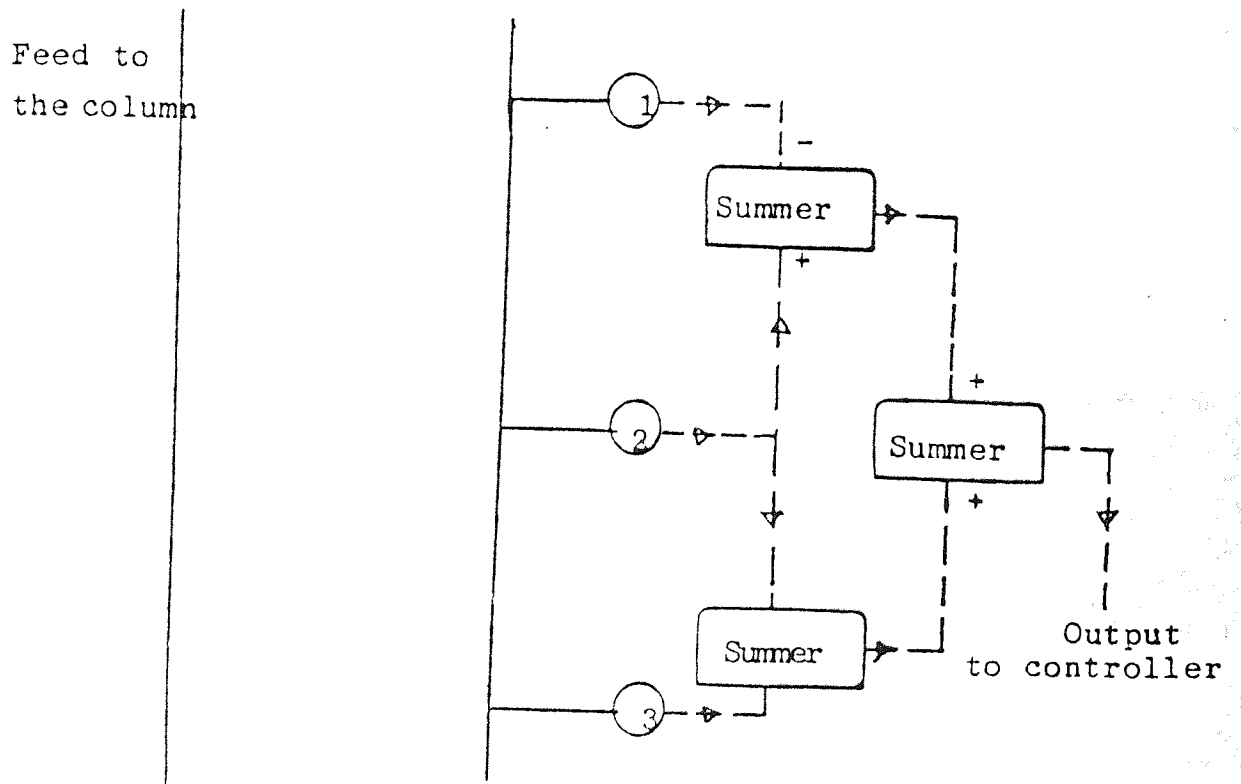


Figure II.2.5

The hardware for the implementation of Luyben's double differential temperature control scheme

$B_1$  = temperature measurement near the feed plate

$B_2$  = an intermediate temperature

$B_3$  = bottoms temperature

Luyben states that this scheme gives a better steady-state control than pressure-corrected temperature. However, he also states that dynamically the ameliorations obtained using this scheme are not significant.

Aside from the multiple-plate and pressure-corrected temperature methods, which can be regarded as being relatively minor variations of the single-plate temperature control scheme, there has not been any progress in furthering the effectiveness of this comparatively simple, but useful technique.

#### II.2.1-3 Material Balance Control

The material balance control scheme introduced by Shinskey (52), is essentially based on steady-state overall and component balances over the column which for a binary system would lead to the following control equation

$$D = F \frac{z-x}{y-x} \quad \text{or} \quad B = F \frac{y-z}{y-x} \dots\dots\dots \text{II.2.1}$$

where

$F, D$  and  $B$  are the feed, distillate and bottoms rates respectively.

$z, x$  and  $y$  are the feed, liquid and vapour compositions of the most volatile component

Additionally, for two-point control, the separation factor is defined as:

$$S = \frac{y(1-x)}{x(1-y)} \dots\dots\dots \text{II.2.2}$$

It is thought that if separation is held constant, the control of y will also result in control of x and vice versa.

Four possibilities for the manipulated variables have been suggested namely:

D, B, boil-up rate V, and reflux rate L. In a later paper (1975) Shinskey (32) introduces heuristics for pairing these variables in order to reduce interaction between them. These are as follows:

- (i) when only one product quality is to be controlled then the material balance should be manipulated
- (ii) the lesser of the two products should be manipulated for product control
- (iii) the material balance should be manipulated to control the quality of the less pure product and the separation factor should be manipulated to control the quality of the more pure product

The authors indicate that enforcing control over the external material balance alone does not ensure the control of product quality. Compositions are determined by the relative flows of vapour and liquid within the column, so these are the streams which ultimately must be regulated. To bring this about, it has been emphasised that automatic level control, say on the reflux drum is imperative. It is also of interest to



note that Shinskey (52) advocates the use of level-controllers to manipulate the reflux flow. There exists a general reluctance in using such arrangements. This is due to the fact that valve-moter hysteresis can lead to a degradation in the liquid level control and this in conjunction with the integrating characteristics of the accumulator could cause intolerable limit cycle (53). Despite these likely problems, it is thought that the arrangement is stable and is being used successfully.

Fauth and Shinskey (20) implemented material balance control on a depropanizer column and, according to them, the results were staggeringly successful so far as the economic impact of the operation was concerned. They also studied local optimization, and floating pressure control and showed that these techniques could also pay off in terms of profitability and reliability.

Gaulier and McCune (54), working on the idea that internal reflux flow within a distillation column can rarely be the same as the external reflux flow, incorporated an internal reflux controller into the conventional material balance scheme. They used the equation suggested by Lupper and Berger (55) which relates the internal and external reflux flows and is as follows:

$$R_I = R\{1 + (C_p/\lambda)(T_o - T_r)\} \dots\dots\dots \text{II.2.3}$$

where

$R_I$  = internal reflux flow

$R$  = external reflux flow

$T_O$  = overhead vapour temperature

$T_r$  = the reflux liquid temperature entering the  
column

$C_p$  = molar specific heat capacity between  $T_O$  and  
 $T_r$

$\lambda$  = latent heat of vaporization at  $T_O$

According to the aforementioned article, they managed to get almost perfect compensation to condenser duty changes. The degree of compensation depended upon how tightly the overhead level had been controlled. The major criticism that may be directed towards their work is the fact that they ignored such limiting factors as flow and level measurement noise.

It must be pointed out that while material balance control is applicable to binary distillation columns, it is virtually impossible to see how the principles could be extended to a multicomponent distillation situation.

## II.2.2 THE MATHEMATICAL PATH : MODEL-DEPENDENT METHODS

By contrast with the deductive path where the synthesis stage is usually accomplished by the single-input-single-output (SISO) design methods, the mathematical path is characterised by the fact that the synthesis stage is normally carried out by the multivariable design methods. The difference is that the multivariable design methods take interaction into account whereas the SISO methods do not.

### II.2.2-1 Non-Optimal Model-Dependent Feedback Methods

Little has hitherto appeared in the literature concerning the non-optimal model-dependent feedback control methods for distillation columns. The use of a model in conjunction with the feedback philosophy has been, in fact, mainly advanced by the need for the proper tray location for temperature measurement. The role of the model has essentially been to assist in finding the proper tray for temperature measurement instead of measuring the temperature profile of the column experimentally as in the deductive path.

Proper tray location by tray-to-tray calculation has been investigated by various workers who have proposed different mathematical models for predicting the dynamic response of the column with different control plate locations. In many cases, the models have been developed from data for open-loop transients which are dominated by the large major time constants

of the column and often show strong non-linear effects (Moczek and Williams (56)). To account for the changes in response time with plate location and type and magnitude of the disturbances, the models must be quite complex and are not convenient for control studies. However, for simulation of closed-loop control systems where deviations from set-points are generally small and the non-linearities are relatively unimportant, simpler models may be satisfactory.

An approximate model based on a linear analysis is presented by Wahl and Harriot (57) which can be used to predict typical column transfer functions and the effect of control plate on critical frequency, maximum controller gain and steady state error in product composition. More recently, this model was tested experimentally by Beaverstock and Harriot (58), who measured the closed-loop response of a column for various plate locations. The conclusions that they reached may be summarised as follows:

- (i) for control of the top product composition by feedback manipulation of the reflux rate, moving the control point down the column decreases the critical frequency and the maximum controller gain because of increasing the number of hydraulic lags, and also increases the steady-state error in product composition. These effects suggest that the control plate should be as close to the top as possible, consistent with measurement accuracy.

- (ii) when the measurement and valve lags are small, two-mode feedback control can correct for moderate (10-20%) changes in the feed rate and feed composition with barely noticeable changes in product compositions. Similar changes in vapour flow produce greater upsets, partly because vapour changes are transmitted rapidly through the column and partly because of the effect of vapour flow on plate hold-up.
- (iii) a linear model seems satisfactory for predicting the effect of control plate location and for comparing control schemes. However, they state that more work is required to predict the hydraulic lags and the effect of vapour rate changes.

#### II.2.2-2 Feedforward Control

In application of feedback control to distillation columns corrective action is taken only after the product qualities have deviated from their desired values, and long times are often required to bring the column to its desired steady state - especially in large towers. Also, undesirable interaction of feedback loops may occur as most columns are multivariable.

Feedforward control in principle eliminates these difficulties by sensing the input disturbances as they enter the column and taking proper corrective action before these disturbances have propagated through the system. Thus control problems inherent in dead time

and distributed parameter systems are theoretically eliminated. However, feedforward control in practice has its limitations. First, the system may not correspond exactly to the mathematical or empirical model used to predict its dynamic behaviour. Second, changes in product compositions caused by unmeasured input disturbances may go uncorrected.

The literature on application of feedforward control to distillation columns is far from voluminous. Luyben and Gerster (59) suggest a transfer function between the input disturbances (feed rate,  $F$ , and feed composition,  $Z_f$ ) and the manipulative or corrective inputs (reflux rate,  $R$ , and vapour boil-up rate,  $V$ ) such that the control objectives, that the perturbations in the compositions of the overhead and bottoms products be zero, are met. The feedforward controller of their distillation system, assuming it to be linear, was made up of four separate transfer functions; in matrix notation these were:

$$\text{FFC} = \begin{bmatrix} R/F & R/Z_f \\ V/F & V/Z_f \end{bmatrix} \dots\dots\dots \text{II.2.4}$$

Therefore, if the transfer functions are known and if upsets in feed rate and feed composition are measured, the proper values of the corrective inputs are readily determined accordingly to:

$$\begin{bmatrix} \delta R \\ \delta V \end{bmatrix} = \begin{bmatrix} R/F & R/Z_f \\ V/F & V/Z_f \end{bmatrix} \begin{bmatrix} \delta F_m \\ \delta Z_{fm} \end{bmatrix} = \begin{bmatrix} \text{FFC} \end{bmatrix} \begin{bmatrix} \delta F_m \\ \delta Z_{fm} \end{bmatrix} \dots \text{II.2.5}$$

where

$F$  and  $Z_f$  are the feed rate and composition at steady state

$\delta F_m$  and  $\delta Z_{fm}$  are the measured upsets in  $F$  and  $Z_f$

$R$  and  $V$  are the reflux and boil-up rates at steady state

$\delta R$  and  $\delta V$  are the corrective inputs

FFC = feedforward transfer function

The transfer functions were determined by solving the system's equations in the frequency domain by the stepping technique - the details of which are explained by Luyben (3).

Their experimental results are indicative of the immense potential of feedforward control for distillation columns. Despite the changes in feed rate and feed composition, the product compositions did not change appreciably and there was no detectable transient period.

Another practical limitation of feedforward control stems from the fact that physical and process limitations such as maximum valve opening may constrain the action required by feedforward control. Under such circumstances, in order to prevent drifts of the product compositions, combined feedforward-feedback controls have been suggested. Little attention has



been given to the problem of combining feedforward with a feedback control system. Lupfer and Johnson (61), Luyben (60) and Shinskey (17) have, however, discussed these concepts qualitatively.

Luyben (62) studied the use of feedforward control on a distillation with feedback control of intermediate control tray temperatures. This effectively meant that the feedback controllers did not control the product compositions directly. The feedforward controller which conventionally changes the manipulative variables, had the additional task of adjusting the feedback controller setpoints. It is interesting to note that they have stated that the addition of feedforward control reduced the feedback interaction.

Ballinger and Lamb (63) produced a theoretical analysis for the combined feedforward-feedback control systems which was implemented by Godman and his colleagues (64) to control a column simulation. It appears that the benefits of feedforward control used additionally to feedback control is largely dependent upon the steady-state effectiveness of the feedforward control system.

The likely drawbacks of feedforward control are due to model inaccuracy and the fact that unmeasured disturbances can go uncorrected. This is where an estimator can play an effective role since it should be capable of eliminating these problems to a large extent.

## II.2.2-3 Modal Analysis and Control

Modal analysis, introduced by Rosenbrock (33) can, in theory, be used not just to determine controller settings but also can serve as a systematic guide for selecting the control system structure or configuration - i.e. for pairing controlled and manipulated variables. The approach is based on the idea that the dynamic behaviour of a system can be represented by the motion of a point in an  $n$ -dimensional space called state-space which leads to a mathematical model in the form of  $n$ -first order differential equations. In this picture the central theme is that the transient behaviour of a process is predominantly determined by the modes associated with the smallest eigenvalues. If it is possible to approximate a high-order system by a lower-order system whose slow modes are the same as those of the original system, then attention can be focussed on the attempt to alter the eigenvalues of the slow modes so as to increase the speed of recovery of the process from disturbances. Obviously, various disturbances excite the modes differently so that a scheme which is based on a lower-order model may be inappropriate if a disturbance injects most of its "energy" in a fast mode which has been neglected. However, implicit in Rosenbrock's approach is the possibility of altering each mode separately so that the resulting control system can be viewed as being non-interacting in the sense that manipulation of one mode may not alter any other mode. Thus, it may be possible with enough

measurements and controls or manipulations to speed up the recovery from any expected disturbance. There are obvious limitations to this, since not all the states can be measured in practice and controls cannot be applied to all the states. This will limit the extent to which the speed of recovery of a mode can be increased.

Modal control can, therefore, be defined as a control that changes the modes of a system to achieve control objectives. In other words, a control scheme in which the manipulated variables are operated in such a way that their action is along the eigenvectors of the uncontrolled system. A brief demonstration of the mathematics associated with modal analysis and control, at this stage, would be in order. These appear more fully in Rosenbrock's original paper and in a more recent paper by Simon and Mitter (66).

It is assumed that the linearised equation of the uncontrolled system, in matrix notation, is:

$$\dot{\underline{X}} = \underline{A} \underline{X} \dots\dots\dots \text{II.2.6}$$

where

$\underline{X}$  = vector of state errors

$\underline{A}$  = relating matrix (nxn)

Supposing that all the natural frequencies (eigenvalues) of the system are real, negative and distinct, then to every eigenvalue of  $\underline{A}$ ,  $\lambda_i$  will correspond an eigen vector  $\underline{V}_i$  which represents one of the modes of the system.

The aim is to reduce  $\underline{X}$  to the zero vector with utmost speed. A possible solution of equation (II.2.6) is:

$$\underline{X}_i = \alpha_i \underline{V}_i \exp(\lambda_i t) \dots\dots\dots \text{II.2.7}$$

i.e. a disturbance in the system grows according to  $\alpha_i \underline{V}_i \exp(\lambda_i t)$  along each eigenvector with  $\alpha_i$  being a constant. Assume that the eigenvalues of  $\underline{A}$ ,  $\lambda_i$  are real, negative and distinct and that

$$\lambda_n < \lambda_{n-1} \dots\dots\dots < \lambda_2 < \lambda_1 < 0 \dots\dots\dots \text{II.2.8}$$

We aim to shift as many as possible of these eigenvalues to greater negativity; so if there are  $p$  manipulatable states, we aim to make  $\lambda_1, \lambda_2, \dots\dots\dots \lambda_p$  as negative as possible.

If we write  $\underline{C}$  as an  $(n \times p)$  matrix having as its columns  $\underline{V}_1, \underline{V}_2, \dots\dots\dots \underline{V}_p$  and  $\underline{B}$  as an  $(n \times p)$  matrix having as its columns the eigenvectors of  $\underline{A}^T$  corresponding to  $\lambda_1, \lambda_2, \dots\dots\dots \lambda_p$ , the following feedback system can be adopted:

$$\dot{\underline{X}} = (\underline{A} + \underline{C}\underline{K}\underline{B}^T)\underline{X} \dots\dots\dots \text{II.2.9}$$

Where  $\underline{K}$  is a diagonal  $(p, p)$  matrix with non-zero elements  $-K_1, \dots\dots, -K_p$ . The eigenvalues of this system are now  $(\lambda_1 - K_1), (\lambda_2 - K_2), \dots\dots\dots (\lambda_p - K_p)$ . Therefore, by using large negative values of  $K_1, K_2, \dots\dots\dots K_p$ , the rate of decay of disturbance can be accelerated.

$\underline{C}$  is in fact the matrix of vectors along which the measurement vector  $\underline{B}^T \underline{X}$  should be forced to move.  $\underline{K}$  thus

becomes the matrix of proportional feedback gains acting on the vector  $\underline{B}^T \underline{X}$ .

Searson (45) found that the dynamics of the modal system compared favourably with the conventional two-term controller systems. For good response, however, elements of  $\underline{K}$  still needed to be tuned.

In the application of modal control to distillation columns, it would appear that one should use many measurements in the state vector; this is not the case because modal control aims to reduce the vector to zero and should the composition profile in the column change, this goal will evidently be impossible to achieve.

Introduction of integral action into the feedback controllers would probably improve the steady-state of the system. But introducing further terms into the controller would mean that more controller gains would have to be tuned. However, decoupling the system should enable the feedback loops to be tuned more rapidly and efficiently - owing to their greater independence of each other.

A modal controller has been proposed by Davidson (40) which uses a feedback from:

- (i) a temperature measurement near the top of the column
- (ii) a temperature measurement near the bottom of the column

and (iii) the pressure at the top of the column to control:

- (i) the reboiler steam temperature
- (ii) the condenser cooling water temperature
- (iii) the top product offtake rate

The author states that the results obtained using this controller are significantly better than those obtained from the more conventional schemes. The criterion used for comparison was the reduction of errors in the products due to changes in the feed composition, the reflux and the condenser temperatures. It must be indicated that his results were obtained on a simulation of an 8-plate column and the changes simulated bear little resemblance to the ones experienced in practice. It is also worth noting that Davidson states that a pressure correction to a measured temperature provides a significant drop in the interaction encountered.

It would be interesting to find out how a modal controller would perform in the presence of an estimator which can be used to estimate the states that cannot be measured. The literature contains no evidence of such attempts to apply modal control plus a filter to distillation columns.

#### II.2.2-4 Optimal Control

Detailed discussion of the optimal control problem and the methods of solution available up to date would be too voluminous to incorporate into this thesis and, also, it exceeds the scope of this thesis. Nonetheless, for completeness, suffice it to make an attempt

to introduce, succinctly, the problem and to review, briefly, the methods that may be adopted to solve the problem whether they be analytical or numerical. These appear more fully in a book by Prime (66).

To date, little has appeared in the literature concerning the optimal control of distillation columns. However, a fairly comprehensive review of the work done in the field is given by Jordan (25) while Walter (26) presents a closed form analytical solution to the problem.

#### II.2.2-4.1 Statement of the Optimal Control Problem

Consider a linear plant which obeys the matrix equation:

$$\dot{\underline{X}}(t) = \underline{P}\underline{X}(t) + \underline{D}\underline{U}(t) \dots\dots\dots \text{II.2.10}$$

where

$\underline{X}(t)$  = the state vector

$\underline{P}$  = the plant matrix

$\underline{D}$  = the driving matrix

$\underline{U}(t)$  = the control effort vector

The general objective is to determine the control vector  $\underline{U}_{opt}$  which minimises a performance criterion,  $J$ .  $J$  is, usually, a quantitative scalar cost function that enables comparisons between systems to be made. A common cost function is Lagrangian of the type:

$$J = \text{Min} \int_0^T L(x_1, x_2, \dots, x_n; U_1, U_2, \dots, U_n) \cdot dt \dots \text{II.2.11}$$



## II.2.2-4.2 Solutions of the Optimal Control Problem

### (a) The analytical Solutions

Much of the work done in this field has been inspired by the contributions of Kalman (68) who introduced the matrix-Riccatti equation as a means of solution. The analytical solutions of the optimal control problem can be broadly categorised into two classes:

- (i) solutions by variational calculus
- (ii) solutions by dynamic programming

Solution by variational calculus involves treating the problem as a minimization problem in variational calculus where the performance criterion equation is to be minimised subject to the constraint equation:

$$\dot{\underline{X}}(t) - \underline{P} \underline{X}(t) - \underline{D} \underline{U}(t) = 0 \dots\dots\dots \text{II.2.13}$$

Thus, having defined the complete set of Pontryargin equations, one then proceeds to derive the matrix-Riccatti equation and hence an optimal feedback controller. Closed form solutions of the matrix-Riccatti equation are investigated by Walter (26) and Jordan (25).

Brosilow and Handley (67) implemented optimal control on a 15-plate, five inch diameter bubble cap column and measured the temperature on every plate : these temperatures were used as the elements of the state vector. The started from:

- (i) a linear plant equation

$$\dot{\underline{X}} = \underline{A} \underline{X} + \underline{B} \underline{U} \dots\dots\dots \text{II.2.14}$$

(ii) integral squared error criterion

$$J = \text{Min} \int_0^{\infty} \{ \underline{X}^T \underline{Q} \underline{X} + \underline{U}^T \underline{R} \underline{U} \} . dt \quad \text{..... II.2.15}$$

(iii) the matrix Ricatti equation

$$\underline{P} \underline{A} + \underline{A}^T \underline{P} - \underline{P} \underline{B} \underline{R}^{-1} \underline{B}^T \underline{P} = -\underline{Q} \quad \text{..... II.2.16}$$

where

$\underline{X}$  = state vector (n x 1)

$\underline{A}$  = process matrix (n x n)

$\underline{B}$  = matrix of process constants (n x m)

$\underline{P}$  = Ricatti matrix (n x n)

$\underline{Q}$  = positive semi definite weighting matrix (n x n)

$\underline{R}$  = weighting matrix (m x m)

$\underline{U}$  = input, vector (m x m)

They assumed  $\underline{R} = \underline{Q}$  in order to achieve an approximate solution.

An unfortunate side-effect of this formulation is that a steady-state offset is produced by a feed composition change because the policy attempts to maintain the weighed vector of state at zero. Brosilow and Handley produced no comparative results to show how their optimal control policy fared in competition with conventional controllers.

Williams (69), in his report, on various control techniques for distillation columns concludes that optimising a control scheme by a dynamic programming method is far too complex. He was attempting to control the top product composition by maintaining a steady boil-up rate. Dynamic programming gave results

similar to those obtained by other control structures. The complexity of dynamic programming is, of course, approximately proportional to the square of the number of states used. Thus Williams' conclusion that dynamic programming is too complex would seem to be damning. He mentions minimising a quadratic performance index but does not discuss its implementation. But it is significant that he finally concludes that model-based control systems provide better controllers than systems tuned on-line and that control systems using second-order models are indistinguishable from those using first-order models.

Lapidus and Luus (70) have presented an algorithm for the solution of the optimal control problems for a non-linear system. This algorithm is a clear indication of the excessive amount of calculations required for solving the optimal control problem.

An obvious use for an estimator in relation to optimal control would be to use it to estimate the states that cannot be measured.

#### II.2.2-5 Adaptive Control

During the last decade adaptive control has often been forecast to become a common development of control systems in the chemical process industries. In this approach one essentially tries to compensate for the process parameter variations. For instance, in a conventional PID controller,

the parameters  $K_C$ ,  $T_I$  and  $T_D$  are updated as the information about the process becomes available. Figure II.2.6 shows a schematic diagram illustrating a possible way of implementation of adaptive control.

Many different types of adaptive control algorithms have appeared in the literature mostly concerning the SISO systems. But few successful applications have been reported, especially as regards distillation columns. In fact the only traceable example to date is due to Van Aarle (71) who studied the adaptive control of a high-vacuum distillation column. He concludes that unless the variations in process parameters are known to hamper control, this type of extensive analysis is difficult to justify. Van Aarle was mainly concerned with plant-adaptive control and identified the following functions that should be performed by an adaptive controller:

(i) identification : deriving information about the process parameters from the observable variables of the process. At this stage, two concepts can be distinguished.

(a) plant-variables adaptive control, where changes in process transfer function are predicted from measurements of the relevant plant variables with the aid of a pre-established relation (e.g. between a dead time and equipment throughput)

(b) plant-characteristic adaptive control, where the process transfer function is estimated

from measurements of the process inputs and outputs possibly with the aid of the psuedo-random binary sequence (PRBS) technique

- (ii) decision : deciding to change the control scheme if the present performance is estimated to be too far below the optimal performance
- (iii) modification : adapting the structure or the parameters of the control system

In contrast with the plant-adaptive control concept, an alternative approach is the model-reference adaptive control which is depicted in Figure II.2.7. Here the response of the model is checked against the real system's response and the difference is used to modify the model and, or, the controller parameters. Takahashi (24) points out the two important examples of such systems, namely the dynamic observer (72) which is used for estimating the state of the system for which the initial state is unknown, and the Kalman filter (73), which is used for state and parameter estimation of a system in a noisy environment.

Multivariable aspects of adaptive control has been briefly discussed by McConcell and Swanick (74) while Price (75) discusses yet another adaptive control technique known as the accelerated gradient method. This is essentially based upon the objective of improving the stability characteristics of model reference adaptive control and can be useful for slowly moving parameters.

It is significant to note that all of the model reference adaptive control methods exploit the principles of feedback.

Figure II.2.6 : A Typical Adaptive Control Scheme

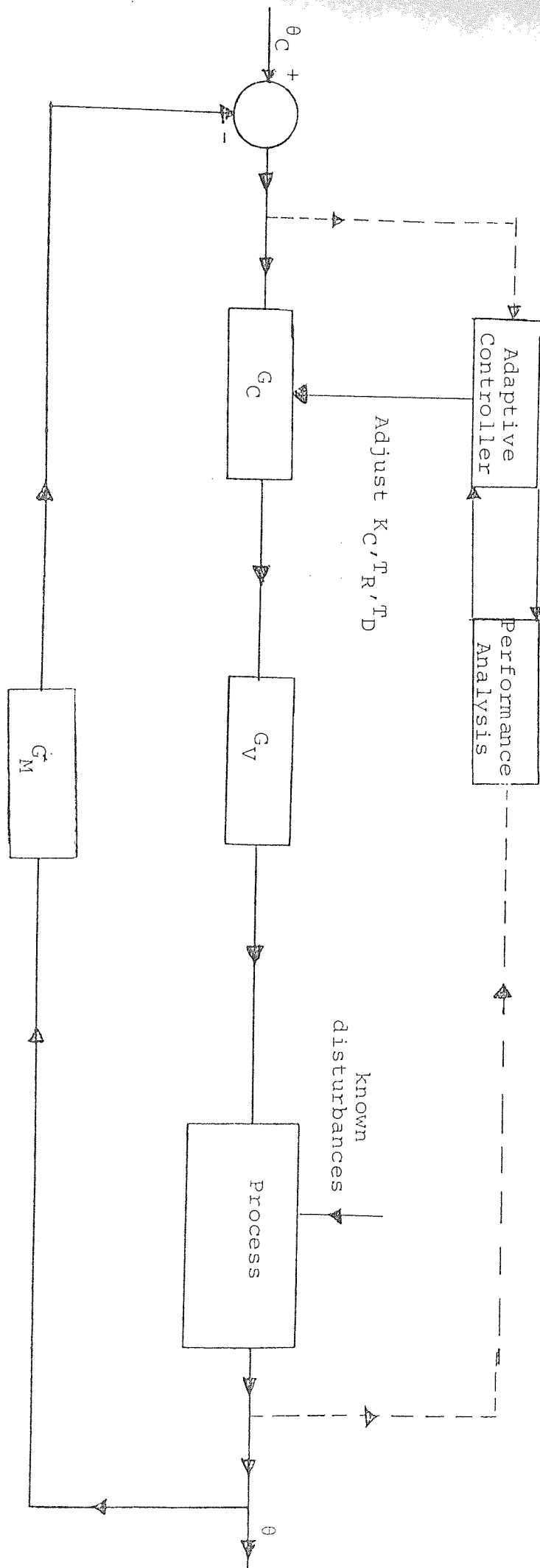
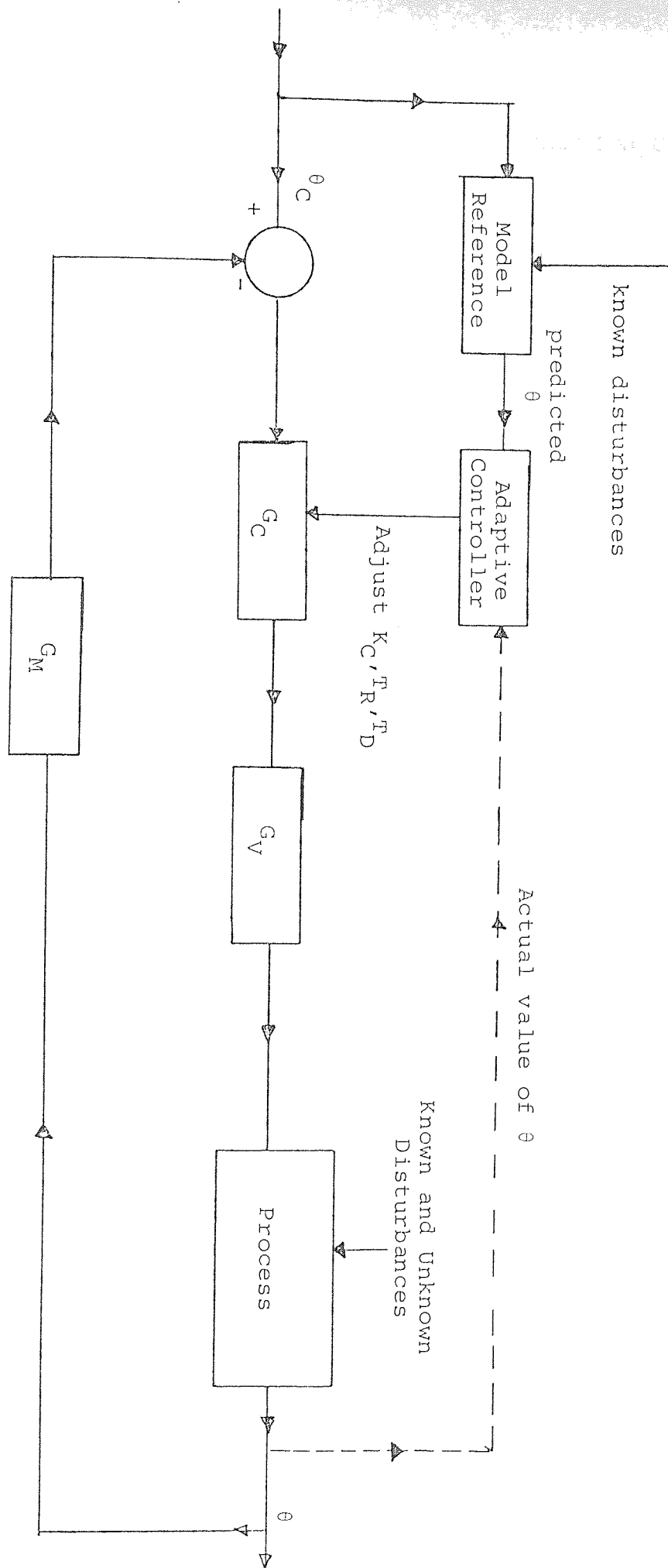


Figure II.2.7 : Proposed Model Reference Adaptive Control Scheme





### II.3 DYNAMIC SIMULATION OF DISTILLATION COLUMNS

One of the important applications of dynamic simulation is in relation to control and comparison of various control configurations for an existing or proposed system design. It enables the study of the dynamic response of the system to various disturbances which can be very valuable for the control system analysis and development.

Simulation of distillation columns, especially for control, can be divided into two parts:

- (i) the preparation of a mathematical model of the distillation process
- (ii) the use of the model to study control of the process

The mathematical modelling of tray distillation columns essentially involves the description of the unsteady state heat and mass transfer phenomena occurring on an individual stage and stepping this up from a single stage to a column with a number of similar stages to provide an approximation to the dynamic behaviour of the column. As regards stagewise distillation five different types of mathematical models can be used to describe the transient behaviour of a single tray : these models can be based upon:

- (i) a perfectly mixed tray
- (ii) plug flow across a tray : this is more relevant to bubble cap and valve trays than sieve trays



- (iii) a perfectly mixed tray with time lag in the downcomer
- (iv) longitudinal dispersion across a tray
- (v) longitudinal dispersion with dead zones on a tray

All of these models except (i) and (iii) involve partial differential equations which are rather complex and require further simplifying assumptions, such as a linear equilibrium relationship, for solution. However, models (i) and (iii), in addition to being more flexible, also enjoy the advantage of being compatible for solution in the time domain by analogue and digital computers.

Both analogue and digital computer simulations of distillation columns have been attempted by different authors with varying degrees of success. Some of the earliest analogue simulation studies were those of Rose and his associates (76,77), who used an analogue computer to represent a five-tray column plus external control devices. Their work is indicative of the fact that analogue simulation of distillation columns can be very laborious and, when large columns are being investigated, the sheer number of analogue components required for a realistic representation of a column can be obtrusive and may, indeed, render the practice impossible.

This is the reason why analogue simulation is less attractive than its digital counterpart where the speed, flexibility and power of digital computers allow detailed dynamic simulations with relatively more ease. Some

of the earliest digital simulation attempts have been due to Rosenbrock (78,79,80), who introduced a computer procedure to solve large sets of simultaneous, non-linear differential equations so as to find the time needed for a column to reach its steady-state after it is started. Since the equations used were the original ones, without restricting assumptions, input step changes of any size could be introduced after the steady state had been reached and the response of the column could be observed.

As far as this thesis is concerned attention will be focussed on the review of the literature on the dynamic simulation of distillation columns using the perfectly mixed plate model, since they are more amenable to solution by digital computers.

### II.3.1 SIMULATIONS BASED UPON UNSTEADY STATE MASS AND ENERGY BALANCES

The perfectly mixed plate model has been presented in various forms by several authors (76,77,78). The usual assumptions made in these derivations are:

- (i) the liquid on each plate is perfectly mixed
- (ii) the time constants for fluid and thermal transfers are negligible compared to that for mass transfer
- (iii) vapour holdup is negligible compared with liquid holdup
- (iv) the column is essentially adiabatic
- (v) the steady-state efficiency does not change during transient periods
- (vi) the liquid holdup on the plate is constant, i.e. the liquid and vapour holdups are not affected during transient periods.

The plate model is then derived by writing unsteady state material and energy balances across the plate.

In the case of binary distillation, the additional assumption of equimolar overflow is usually made to eliminate the need for the energy balance.

In what appears to be a refinement of this approach, more recently, various authors such as Franks (2) and Ramirez (5) have proposed the following equation for the calculation of the liquid overflow rate from each stage:

$$\tau \frac{dL_n}{dt} = L_{n-1} - L_n \dots\dots\dots \text{II.3.1}$$

where

$L_n$  = liquid rate leaving the nth stage

$L_{n-1}$  = liquid rate entering the nth stage

$\tau$  = hydraulic time constant

This equation is derived from a momentum balance on the liquid phase as illustrated by Ramirez (5).

Waggoner and Calvin (81) developed a simulation for a distillation column with the following characteristics:

- (i) a stage-to-stage computation
- (ii) a two component approximation to reduce the computation time
- (iii) equilibrium described by specified stage relative volatility
- (iv) overflow response developed from hydraulic effects
- (v) minimal or no iteration within the time step
- (vi) boil-up response that only shows a time lag in the reboiler

The programme developed by them included a numerical approximation for the time varying term in the material and energy balances.

Also, the equilibrium coefficient which is a non-linear function of the composition was recomputed whenever the composition changed. They have not produced any quantitative results to enable an assessment of such an approach.

### II.3.2 SIMULATIONS INCLUDING FLUID DYNAMICS

The major criticism that may be raised against the previous approach to the dynamic simulation of distillation columns is the assumption of constant liquid holdup on the plates, since during throughput changes, the vapour and liquid rates and hence the plate holdups are expected to vary with time. Thus, although the assumption of constant liquid holdup may have little effect on the steady-state operation, dynamically, it appears unrealistic - particularly in the face of feed and reflux rates changes.

In order to remove this assumption, one has to resort to the consideration of the fluid dynamic phenomena occurring on a plate during operation. Luyben (3), and Lamb and his co-workers (82) have suggested that an unsteady state material balance should be made over each plate and that the liquid overflow rate from each plate should be calculated from the Francis (1) weir formula, i.e.

$$\frac{dM_n}{dt} = (L_{n-1} - L_n) + (V_n - V_{n-1}) \dots\dots\dots \text{II.3.2}$$

$$L_n = f \text{ (weir height, crest length and } g) \dots\dots\dots \text{II.3.3}$$

where

$M_n$  = holdup on plate  $n$

$L$  = liquid rate

$V$  = vapour rate

It must be pointed out that the calculation of the liquid overflow by this method is only approximate, but it is simple and easy to use provided that the tray time constant is available or that it can be measured.



## II.4 ESTIMATION

Multivariable control systems designed using state-space techniques often require that all of the system state variables be available to control the system. However, in many practical problems it may not be economical or convenient to measure all of the state variables. An alternative approach is to use an estimation technique to provide estimates of the state variables which are not measured. Kailath (83) gives a comprehensive review of the development of linear estimation theory during the past three decades while Rhodes (84) produces a useful tutorial introduction to estimation.

Of all the state estimation methods proposed in the literature, the Kalman filter (87,88,89) and the Luenberger observer (85,86) have received the most attention. Despite successful applications of the Kalman filter in the aerospace industry, there have been very few reported applications in the process industries (90,91). Similarly, few if any experimental applications of the Luenberger observer have been reported.

Both continuous-time and discrete-time forms of the Kalman filter are available (Jazwinski (16)). As regards this thesis, however, attention will be focussed upon the discrete-time version of the Kalman filter and its extended form : the so-called extended Kalman filter.

#### II.4.1 KALMAN FILTERING

The derivation of the Kalman filter has been reported by many authors (9,16). The discrete-time Kalman filter is composed of matrix recursion relations, the simplicity of which makes them particularly amenable to implementation on a digital computer. The requirements for a Kalman filtering exercise are:

- (i) a lumped parameter model of the system in the time domain, i.e. a model comprising  $n$  linear differential equations
- (ii) measurement statistics, i.e. the degree of uncertainty in the measurements
- (iii) a good idea of the intensity of the random disturbances to which the system is exposed
- (iv) the model accuracy statistics

The Kalman filter algorithm provides an optimal estimate of the state of a linear, time-variant dynamic system observed sequentially in the presence of additive Gaussian noise; such systems are referred to as linear stochastic dynamic systems. The estimate obtained at each sample time is optimal in the sense that it is the maximum likelihood estimate conditioned on all observations up to that time. Such a system can be described by the linear stochastic differential equation:

$$dx_t = A(t)x_t dt + D(t)u_t dt + G(t)d\beta_t$$

..... II.4.1

$$y_t = M(t)x_t + V_t$$

where

$t$  denotes time

$x$  = vector of state variables (nx1)

$y$  = vector of measured variables (mx1)

$v$  = vector of random measurement (mx1)

disturbances, represented by

a zero mean, white Gaussian

noise process

$u$  = vector of deterministic system (qx1)  
inputs

$A$  = continuous matrix time-function (nxn)

$D$  = continuous system input driving (nxq)  
matrix

$G$  = continuous matrix time-function (nxr)

and

$\{\beta_t, t \geq t_0\}$  is an  $r$ -vector of Brownian motion or  
Weiner process (16)

with

$$E\{d\beta_t d\beta_t^T\} = F(t).dt \dots\dots\dots \text{II.4.2}$$

where

$F(t)$  is a  $rxr$  continuous time-function matrix

Equation II.4.1 can now be integrated over the interval  
 $\{t_k, t_{k+1}\}$  to convert the system into the discrete form.

$$\begin{aligned} x(t_{k+1}) = & \phi(t_{k+1}, t_k) x(t_k) + \int_{t_k}^{t_{k+1}} \phi(t_{k+1}, \tau) D(\tau) u_\tau d\tau \\ & + \int_{t_k}^{t_{k+1}} \phi(t_{k+1}, \tau) G(\tau) d\beta_\tau \\ & \dots\dots\dots \text{II.4.3} \end{aligned}$$

where the (nxn) matrix  $\Phi$  is the state transition matrix, i.e.

$$\frac{d}{dt} \Phi(t, \tau) = A(t) \Phi(t, \tau) \dots\dots\dots \text{II.4.4}$$

where

$$\Phi(\tau, \tau) = I$$

$$\Phi(t, \tau) \Phi(\tau, \zeta) = \Phi(t, \zeta) \text{ for all } t, \tau, \zeta$$

also

$$\Phi^{-1}(t, \tau) = \Phi(\tau, t)$$

We can now write

$$W_{t_{k+1}} = \int_{t_k}^{t_{k+1}} \Phi(t_{k+1}, \tau) G(\tau) \cdot d\beta_{\tau} \dots\dots\dots \text{II.4.5}$$

Thus

$$x(t_{k+1}) = \Phi(t_{k+1}, t_k) x(t_k) + \int_{t_k}^{t_{k+1}} \Phi(t_{k+1}, \tau) D(\tau) u_{\tau} \cdot d\tau + W_{t_{k+1}} \dots\dots\dots \text{II.4.6}$$

where

$\{W_{t_{k+1}}\}$  is an n-vector of random system disturbances represented by a zero mean white Gaussian process.

Assuming that the deterministic system inputs are time-invariant between time  $t_k$  and  $t_{k+1}$  and for generality, let us also assume that there exists a discrete system noise coefficient matrix  $\Gamma(t_k)$ . We can then write

$$x(t_{k+1}) = \Phi(t_{k+1}, t_k) x(t_k) + \Gamma_D(t_k) u(t_k) + \Gamma(t_k) W_{t_{k+1}} \dots\dots\dots \text{II.4.7}$$

$$Y(t_k) = M(t_k) + V_{t_k} \dots \dots \dots \text{II.4.8}$$

where

- $\Phi =$  the state transition matrix (nxn)  
 $\Gamma_D = \int_{t_k}^{t_{k+1}} \Phi(t_{k+1}, \tau) D(\tau) . d\tau$  the discrete input driving (nxq)  
 matrix  
 $M(t_k) = M(t)$  the discrete measurement (mxn)  
 matrix  
 $\Gamma =$  system noise coefficient (nxr)  
 matrix  
 $W_{t_k} =$  r-vector of random system  
 disturbances represented by a  
 zero mean white Gaussian noise

For time invariant systems  $\Phi = \exp(A\delta t)$

where  $\delta t = t_{k+1} - t_k$

Also

$$E\{W_{t_k}\} = 0$$

$$E\{V_{t_k}\} = 0$$

For simplicity of notation we will henceforth represent the discrete time  $t_k$  by  $k$ . The respective covariances of  $V_k$  and  $W_k$  are given by:

$$Q(k) = E\{W_k W_k^T\} ; \text{ the (nxn) system noise covariance matrix}$$

$$R(k) = E\{V_k V_k^T\} ; \text{ the (mxm) measurement noise covariance matrix}$$

where

$Q(k)$  and  $R(k)$  are positive semi-definite and positive definite respectively

Finally, assuming that the initial state estimate  $x(0,0)$  together with its error covariance,  $P(0,0)$  are known a priori, then the Kalman filter determines the estimate of the state and minimizes the quantity  $J$  as follows:

$$J = \frac{1}{2} \{ \bar{x}(k) - x(k,k) \}^T P(k,k)^{-1} + \frac{1}{2} \sum_{i=1}^{k-1} \{ y(i+1) - M(i+1)x(i+1,i) \}^T R(i+1) \{ y(i+1) - M(i+1)x(i+1,i) \}$$

..... II.4.9

where

$\bar{x}(k)$  is the true state of the system

$x(i,\ell)$  denotes the estimate of the state  $x$  at time  $i$  given the measurements up to time  $\ell$  where  $\ell < i$

$P(i,\ell)$  denotes the covariance of the error in this estimate

The filter variables are:

<u>Variable</u>	<u>Definition</u>	<u>Dimension</u>
$x(k,k)$	State estimate of $t_k$ given $y(k)$	$n \times 1$
$p(k,k)$	Covariance matrix of error in $x(k,k)$	$n \times n$
$\Phi(k+1,k)$	State transition matrix (from $t_k$ to $t_{k+1}$ )	$n \times n$
$\Gamma_D(k)$	System input driving matrix	$n \times q$
$Q(k+1)$	System noise covariance matrix	$r \times r$
$x(k+1,k)$	State estimate at $t_{k+1}$ given $y(k)$	$n \times 1$
$P(k+1,k)$	Covariance of the error in $x(k+1,k)$	$n \times n$

<u>Variable</u>	<u>Definition</u>	<u>Dimension</u>
$M(k+1)$	Measurement matrix	$m \times n$
$R(k+1)$	Measurement noise covariance matrix	$m \times m$
$K(k+1)$	Filter (Kalman) gain matrix at $t_{k+1}$	$n \times m$
$y_{k+1}$	Measurement or observation at $t_{k+1}$	$m \times 1$
$\Gamma(k)$	System noise coefficient matrix	$n \times r$

By examination of equation II.4.13 it can be seen that the estimate of the state vector  $x(k+1, k+1)$ , is the sum of the predicted state and the weighted measurement error,  $K(k+1)\{y(k+1) - M(k+1)x(k+1, k)\}$ . The original derivation of the algorithm (92) points out a number of valuable features of estimates thus calculated. These are that the estimate is uniformly asymptotically stable and that the convergence of the variances of the estimates, as each measurement is processed, is insensitive to round-off errors, provided that the system is observable and controllable.

The dual concept of observability and controllability were introduced by Kalman (92) in his original work as a part of his general filtering theory. Coggan and Noton (93) interpret these concepts as follows:

- (i) a system is observable, if with perfect measurements and no random disturbances, all the state variables can be estimated after a finite number of measurements
- (ii) a system is controllable if all the states are excited by the random disturbances  $z(k)$



## II.4.2 THE KALMAN FILTER ALGORITHM and error covariance,

required to

The Kalman filter algorithm can be written as a set of prediction and estimation equations as follows:

Prediction:

$$x(k+1,k) = \Phi(k+1,k)x(k,k) + \Gamma_D(k)\bar{u}(k) \quad \dots\dots \text{II.4.10}$$

$$P(k+1,k) = \Phi(k+1,k)P(k,k)\Phi^T(k+1,k) + \Gamma(k+1,k)Q(k+1)\Gamma^T(k+1,k) \quad \dots\dots \text{II.4.11}$$

Estimation:

$$K(k+1) = P(k+1,k)M^T(k+1) \{M(k+1)P(k+1,k)M^T(k+1) + R(k+1)\}^{-1} \quad \dots\dots \text{II.4.12}$$

$$x(k+1,k+1) = x(k+1,k) + K(k+1)\{y(k+1) - M(k+1)x(k+1,k)\} \quad \dots\dots\dots \text{II.4.13}$$

$$P(k+1,k+1) = \{I - K(k+1)M(k+1)\}P(k+1,k) \quad \dots\dots\dots \text{II.4.14}$$

or

$$P(k+1,k+1) = \{I - K(k+1)M(k+1)\}P(k+1,k)\{I - K(k+1)M(k+1)\}^T + K(k+1)R(k+1)K^T(k+1) \quad \dots\dots\dots \text{II.4.15}$$

The more important concept to the field of filtering theory is that of observability. If one of the state variables of the system cannot affect the measurement vector then the consequential unobservability leads to the estimates produced by the filter being sub-optimal.

The time taken for the filter to converge has been shown by Storey (94) to depend on the accuracy of the

initial estimate,  $x(0,0)$ , and the initial error covariance,  $P(0,0)$ , a priori knowledge of which is required to initiate the filter. The larger the initial error in the estimates, the longer the filter takes to converge. This is because until the system has become observable, the filter relies on the initial estimate. In the case of a large initial error covariance matrix, the filter will display a slower response since it will rely initially upon current noisy measurements.

In the statement of the filter algorithm, alternative equations have been given for determining the error covariance of the state estimations (equations II.4.14 and II.4.15). It has been shown by Aoki (108) that equation II.4.15 is preferable since the right hand side is the sum of two symmetric positive definite matrices while equation II.4.14 is at best the difference of two positive definite matrices. Therefore, equation II.4.15 is better conditioned for numerical computation and will retain the positive definiteness and symmetry of  $P(k,k)$ .

Following the original work of Kalman, the main contributions to the field of linear filtering theory have been aimed at generalizing Kalman's earlier work. The most significant of these developments (95,96) have been in extending the theory to allow for correlation between the system and measurement noises. The problem of coloured (time-correlated) is partially solved by Kalman (97). Jazwinski (16) provides a comprehensive review of these generalizations.

#### II.4.3 EXTENDED KALMAN FILTER

The Kalman filter formulation is in terms of a linear state-space model and is thus only applicable to systems which can be described by a set of first order, linear differential equations and in which the outputs are linearly related to the state variables. For such systems the theory developed by Kalman provides an optimal filter. To most engineering problems, however, such a linear model is not immediately applicable except as a very rough approximation. The dynamic system for most engineering problems is frequently found to be described by a series of  $n$ th order differential equations. The fact that  $n$ th order derivatives appear does not offer any theoretical difficulties because any  $n$ th order differential equation may be written as a system of  $n$  first order differential equations. Nonetheless, the output of the system commonly appears in terms of quantities that have a non-linear algebraic relation with the state variables and thus the application of the Kalman filter to such systems may seem illogical due to its completely linear basis. However, its computational ease and conceptual simplicity has led to a modification of the Kalman filter which is commonly referred to as the extended Kalman filter. The application of the extended Kalman filter to non-linear systems is essentially characterized by the following points:

- (i) it requires linearization around each last estimate prior to the next estimation by Taylor series expansion neglecting the second and higher order terms
- (ii) if the state variables are not being measured directly, instead of the "state" and "measurement", we then consider the state deviation and the measurement deviation from a reference trajectory which is physically meaningful. The choice of the latest estimated state or the steady state as the reference trajectory is not uncommon
- (iii) the estimates may no longer be optimal

Consider the non-linear stochastic system described by

$$dx_t = F(x_t, u_t)dt + G(t)d\beta_t \dots\dots\dots \text{II.4.16}$$

$$y_t = H(x_t) + V_t \dots\dots\dots \text{II.4.17}$$

or the discrete form

$$x_{k+1} = f(x_k, u_k) + \Gamma(k)w_{k+1} \dots\dots\dots \text{II.4.18}$$

and observations

$$y_k = h(x_k) + v_k \dots\dots\dots \text{II.4.19}$$

where  $\beta, u, v$  and  $w$  are as defined for the linear system.

If the system equations are linearized about the current estimate of state  $x_k$ , by means of a truncated Taylor series expression (16), the linear Kalman filter algorithm is applicable except:

- (i) the state prediction stage is carried out as

$$x(k+1,k) = x(k,k) + \int_0^{\delta t} F(x_t, u_t) . dt \dots\dots\dots \text{II.4.20}$$

where

$x(k,k)$  is the estimate of state at  $t_k$

$$\delta t = t_{k+1} - t_k$$

- (ii) the state transition matrix may be approximated by

$$\Phi(k+1,k) = I + \frac{\partial f(x_k, u_k)}{\partial x_k} . \delta t \dots\dots\dots \text{II.4.21}$$

where the Jacobian  $\frac{\partial f(x_k, u_k)}{\partial x_k}$  is evaluated about the latest estimated state or a predetermined reference trajectory.

- (iii) the measurement matrix is evaluated as

$$M(k+1) = \frac{\partial h(x_k)}{\partial x_k} \dots\dots\dots \text{II.4.22}$$

where the derivatives are evaluated about a reference trajectory or the latest estimated state.

### Notation

$x_t$	continuous variable
$x(t_k)$	discrete variable
$x(k)$ and $x_k$	abriviations for $x(t_k)$
$H, f$	continuous time functions
$h, f$	discrete time functions

#### II.4.4 ESTIMATION APPLIED TO CHEMICAL PROCESSES

Applications of estimation to chemical processes have been predominantly concerned with Kalman filtering. Webb (27) gives a comprehensive review of the work done in this area - particularly in open loop situations. Of interest to this thesis is the use of estimation in closed-loop or control situations and thus we will concentrate on review of the work on this aspect of estimation.

One of the most notable of the earlier chemical engineering applications of the Kalman filter was by Noton and Choquette (98,99) in the identification of a reactor train. The initial work was done using an off-line computer applied for open loop control experiments. Following the success of these experiments further work was done during closed loop experiments using a remote time-sharing computer. Although this work cannot be described as an on-line application, the overall exercise was successful inasmuch as a significant improvement over manual control was reported.

The theoretical problems encountered when dealing with systems containing a large number of state variables, unknown parameters, transport lags and strong non-linearities was tackled with considerable success by Coggan and Noton (93). In this paper the extended Kalman filter is applied to simulated systems exhibiting large random disturbances and having unknown initial values. The possibility of trading model simplification for

unnecessary numerical accuracy is also discussed.

An approach to model reduction is suggested by Coggan and Wilson (100), who minimise the number of state variables required to describe a system. The extended Kalman filter is modified to evaluate measurement error statistics and detect the presence of bias. The same authors also report the on-line implementation of this filter. The mini computer used had 4k words of memory and was applied to a tenth order system.

Most of the work reviewed by Webb (27) is concerned with open-loop state and parameter estimation. Lynch and Ramirez (101), however, were one of the first groups of workers who investigated estimation in a closed-loop control situation. They developed and implemented a time-optimal control algorithm for a continuous stirred tank reactor. Estimation was carried out by an extended Kalman filter. The reaction studied is the decomposition of hydrogen peroxide with a homogeneous catalyst of potassium iodide. The experimental work done was in an on-line environment using a General Data Corporation Nova 1210 Minicomputer with 8k words of memory. Lynch and Ramirez conclude that extended Kalman filter works very well in estimating the unmeasured system states of the non-linear model. The authors do not implement the complete filter algorithm in an on-line situation. The filter gain matrix,  $K$ , is assumed to be constant for a system at or near steady-state and is computed off line from a steady-state value of the estimation error covariance matrix,  $P(k,k)$ .



The first experimental studies of the on-line implementation of non-stationary forms of the Kalman filter are reported in the work by Payne (28) and Coleby (29). Both of these workers studied the on-line, real-time implementation of an essentially uncontrolled double effect evaporator, whose instrumentation was interfaced to a Honeywell 316 computer with 16k words of memory.

The earlier work of Payne was involved with the application of the extended form of the Kalman filter. His work highlighted the many difficulties that are encountered during on-line implementation of the Kalman filter, many of which have been overlooked by workers involved in simulated studies. Two of the most important points are the cycle time required by the filter algorithm for large systems and the assumptions required in order to make the system operate within the limits imposed by the equipment used.

Following the work of Payne, the problem of a poor system model was tackled by Coleby. Coleby states that where there is doubt about the accuracy of the prediction equations, some method to control the filter divergence should be incorporated into the filter algorithm.

A complete experimental study of modern control theory was carried out during the years of 1972 to 1974 by Soberg, Fisher and co-workers in the Department of Chemical Engineering at the University of Alberta in Canada. The research carried out was specifically

concerned with the implementation of computer control of a pilot plant size, double effect evaporator and the subsequent evaluation of multivariable design techniques. In a collective report (102) the authors indicate that the incorporation of the Kalman filter into a multivariable computer control system provides significantly better control. It is significant to note that these workers used the noise covariance matrices  $R$  and  $Q$  as design parameters. This indicates that the on-line application of the Kalman filter involves a certain amount of "tuning".

More recently, Litchfield and co-workers (116) applied five different Kalman filters to the problem of estimating the state of a real chemical reactor operating under open-loop and feedback control. The filters considered included the fixed gain, the extended and the exponentially data weighted. It is significant that they conclude that the extended Kalman filter was the most successful when used in open-loop and feedback time-optimal control schemes.

#### II.4.5 ESTIMATION APPLIED TO DISTILLATION COLUMNS:

##### THE COMPUTER PATH

The earliest attempt to apply estimation to distillation columns were those of Brosilow and Weber (34), who proposed a linear static least square estimator to relate perturbations in the measured quantities to perturbations in product quality. The estimator is derived from a linear model of the process which is valid in some region about a steady-state operating point. The implication of this is that the static estimator is only applicable to cases with mild nonlinearities or small deviations from the steady state.

Luyben and Shah (106), in pursuit of this proposal, used a non-linear estimator to control a binary distillation column and found that estimator-based schemes achieved superior composition control to that achieved with conventional control schemes.

More recently, in a series of three papers, Brosilow and his co-workers (103,104,105) introduced the notion of Inferential Control which essentially means using selected temperature and flow measurements to estimate, or infer, the effect of measurable disturbances on product quality and adjust the control effort to counteract the effect of the measured disturbances. It must be pointed out that although these static estimators can be made insensitive to modelling and measurement noises, they propose no means of improving an inaccurate model and are solely intended

for the estimation of product compositions from secondary measurements. These authors also consider the use of optimal dynamic estimators. However, the fact that they attempt to analyse the estimators in the Laplace domain tends to obscure the issue to some extent since it is generally believed that the dynamic estimators are best analysed and understood in the time domain.

A thorough experimental investigation of the available control schemes for distillation columns has been carried out by Dahlgvist (107). He measured the compositions on various plates and used the Kalman filter for state reconstruction that is needed for multivariable feedback controller design. It is significant that he reaches the following conclusions:

- (i) multivariable controllers designed from purely theoretical models give better results than the SISO controllers that were tuned on-line to the process
- (ii) coupling of reflux flowrates to boil-up proved to be effective when there was an unmodelled time delay in the system
- (iii) a third composition measurement located near the feed tray improves the performance of the control system
- (iv) the control variables are faster adjusted to new steady state levels if feedforward compensation is applied

It appears, however, that by using the Kalman filter off-line and for state reconstruction only, he

does not exploit the full potential of the Kalman filter - especially for on-line applications.

## NOTATION

$\underline{A}$	= relating matrix
$\underline{B}$	= the matrix of left eigen vectors of $\underline{A}$
$B$	= bottoms rate
$B_1, B_2, B_3$	= temperature measurements near the feed plate, an intermediate temperature and bottoms temperature respectively
$\underline{C}$	= the matrix of right eigen vectors of $\underline{A}$
$C_p$	= molar specific heat capacity
$D$	= distillate
$\underline{D}$	= driving matrix
$F$	= feed rate
$Z$	= feed composition
$G_c$	= controller transfer function
$G_v$	= valve transfer function
$G_M$	= measurement transfer function
$J$	= scalar performance criterion
$\underline{K}$	= proportional gain matrix
$L_n$	= liquid leaving the nth tray
$\underline{P}$	= plant matrix or the Ricatti matrix
$\underline{Q}$	= positive semi definite weighting matrix
$\underline{R}$	= weighting matrix
$R$	= reflux rate
$R_I$	= internal reflux
$S$	= separation factor
$T_o$	= overhead temperature
$T_r$	= reflux temperature

$\underline{u}_i$  = eigen vectors of  $\underline{A}^T$   
 $\underline{u}(t)$  = control effort  
 $\underline{V}_i$  = eigen vectors of  $\underline{A}$   
 $V_n$  = vapour rate leaving the nth tray  
 $x$  = liquid composition  
 $y$  = vapour composition  
 $\underline{X}$  = vector of state variables

#### Subscripts

$m$  = measured value

#### Greek Symbols

$\lambda_i$  = eigen values of  $\underline{A}$   
 $\tau$  = hydraulic time constant

#### Filtering Notation

$A$  = continuous matrix time function  
 $D$  = continuous system input driving matrix  
 $G$  = continuous matrix time function  
 $K$  = filter gain matrix  
 $M(t)$  = continuous measurement matrix  
 $M(t_k)$  = discrete measurement matrix  
 $P$  = error covariance matrix  
 $Q$  = system noise covariance matrix  
 $R$  = measurement noise covariance matrix  
 $t$  = continuous time  
 $t_k$  = discrete time  
 $u$  = vector of deterministic system inputs  
 $v$  = vector of white Gaussian noise  
 $w$  = vector of random system disturbances  
     represented by a zero mean white Gaussian process  
 $x$  = vector of state variables  
 $y$  = vector of measured variables



### Greek Symbols

$\beta_t$  = vector of Brownian motion or Weiner process

$\phi$  = state transition matrix

$\Gamma$  = system noise coefficient matrix

$\Gamma_D$  = discrete system input driving matrix

# CHAPTER THREE

THE CONSTRUCTION AND INSTRUMENTATION OF THE  
DISTILLATION COLUMN AND ITS INTERFACING  
TO THE HONEYWELL-316 COMPUTER

### III.1 INTRODUCTION

The process equipment is shown in Figure III.1.  
It will be described through the following stages:

- (i) the construction of the column
- (ii) its instrumentation
- (iii) its interfacing to the departmental Honeywell 316  
computer via the Honeywell Analogue/Digital  
Input System (HADIOS)

The distillation column and its accessories were donated to the Department by the I.B.M., U.K. Ltd., together with some parts for its instrumentation and data conditioning.

All of the hardware involved will be described in this Chapter. The software associated with HADIOS will be discussed in Chapter V.

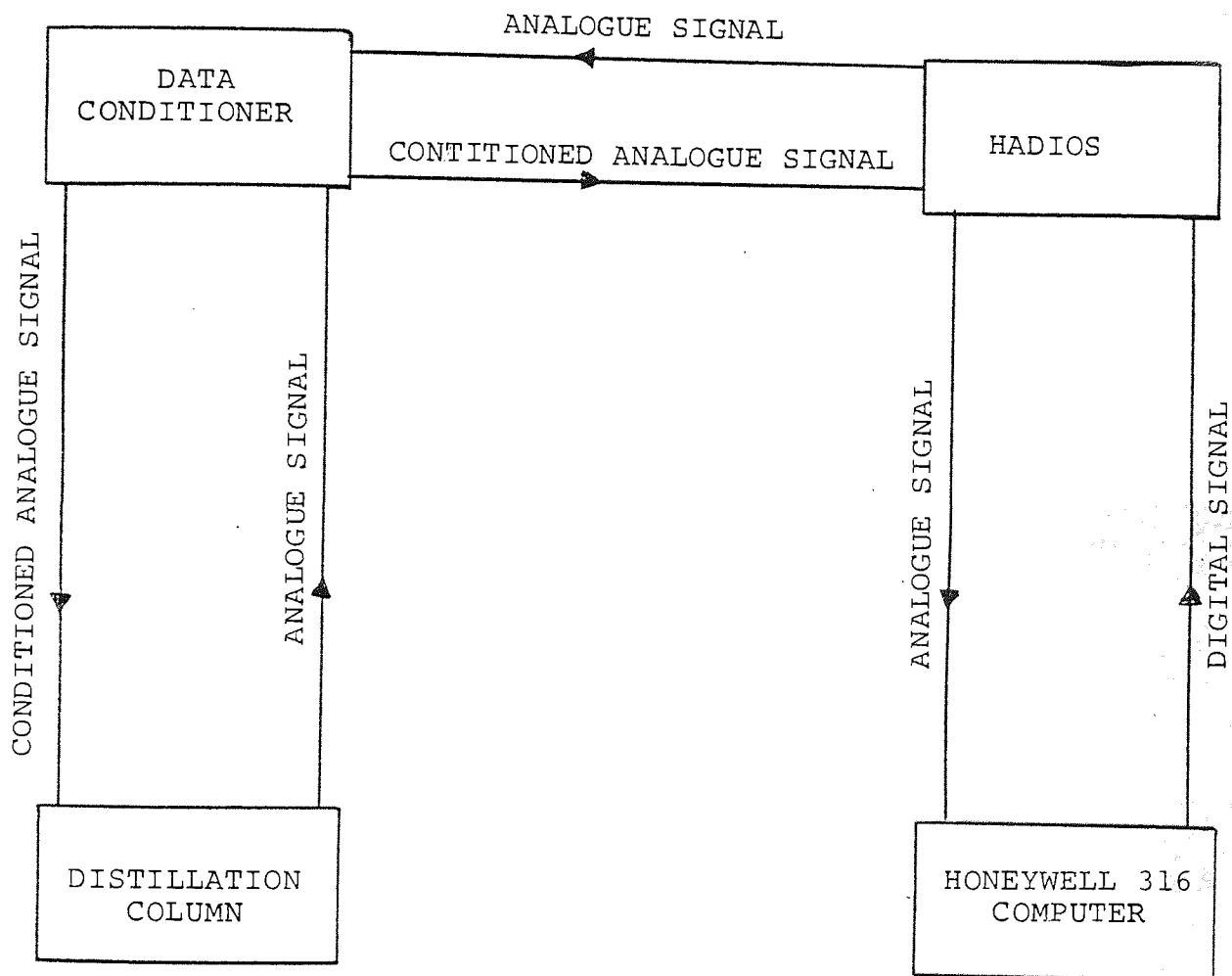


FIGURE III.1 - The Entire Experimental arrangement in Block Diagram

### III.1.1 THE CONSTRUCTION OF THE DISTILLATION COLUMN

At present, the column and its accessories comprise:

- (i) an enriching and a stripping section with six and four 3-inch diameter sieve trays respectively and one temperature measurement well per tray
- (ii) a 3-inch diameter standard glass total condenser plus the reflux drum
- (iii) a 2.4 kw, double-circuit Isomantle electric heater
- (iv) a 1 metre long, 3-inch O.D. glass pipe section situated above the enriching section to enable gravity flow in the reflux and distillate lines
- (v) two cylindrical feed tanks to enable composition changes to be introduced
- (vi) a spherical top product tank
- (vii) a spherical bottom product tank
- (viii) three centrifugal stainless steel pumps

The schematic diagram of the column is given in Figure III.2 while that of a typical tray is depicted in Figure III.3. The column and tray's leading characteristics and dimensions are given in Tables III.1 and III.2 respectively.

The column was intended to be an all-purpose distillation column capable of handling corrosive liquids. Therefore, the materials used for its construction and piping were strictly limited to stainless steel, glass and P.T.F.E. All of the pipe lines are

made of  $\frac{1}{2}$  inch O.D. heavy gauge stainless steel with the exception of the overhead vapour line connecting the column to the condenser which is made of glass and is 3 inches in diameter.

The feed tanks have been situated at a relatively higher elevation from the feed pump so that the drop in the liquid level in the tanks does not affect the total head on the suction end of the pump appreciably and thus the flow through the feed line remains effectively constant during a run.

The condenser cooling water is supplied by a standard constant head tank. The cooling water is received from the departmental cooling tower.

A small heat exchanger has been installed in the bottom product line. Its purpose is to ensure that boiling liquid does not reach the pump and thus the likely pump cavitation problems are avoided. The cooling-water supply for this heat exchanger is also supplied by the departmental cooling tower.

The entire column and the vapour line from the column to the condenser have been lagged with  $\frac{1}{2}$ " standard fibre glass lagging. Plates 1,2 and 3 show the entire column and its accessories from three different angles.







Process Notation	Function and Material	Dimensions
$T_1$ and $T_2$	Feed Tanks: glass	Volumes = 30 lit. approx.
$T_3$	Reboiler: glass	Diameter= .32 m. approx.
$T_4$	Reflux Drum: glass	Diameter= .762 m.
$T_5$	Bottoms Tank: glass	Volume = 50 lit. approx.
$T_6$	Distillate Tank: glass	Volume = 50 lit. approx.
$V_i; i=1,5$	Motorized Valves: stainless steel	
$S_i; i=1,5$	Sample Valves: stainless steel	
$P_i; i=1,3$	Centrifugal Pumps: stainless steel	
$H_1$	Total condenser: glass	Diameter= .762 m.
$H_2$	The Electric Heater	
$H_3$	Heat Exchanger	
TI	Temperature Indicator	
FI	Flow Indicator	
LI	Level Indicator	
<u>Other Miscellaneous Dimensions:</u> Length of the enriching section = 0.65 m. approx. Length of the stripping section = 0.55 m. approx. Length of the gravity flow pipe = 1.0 m. approx.		

Table III.1 - The Process Notation and Main Particulars of the Column

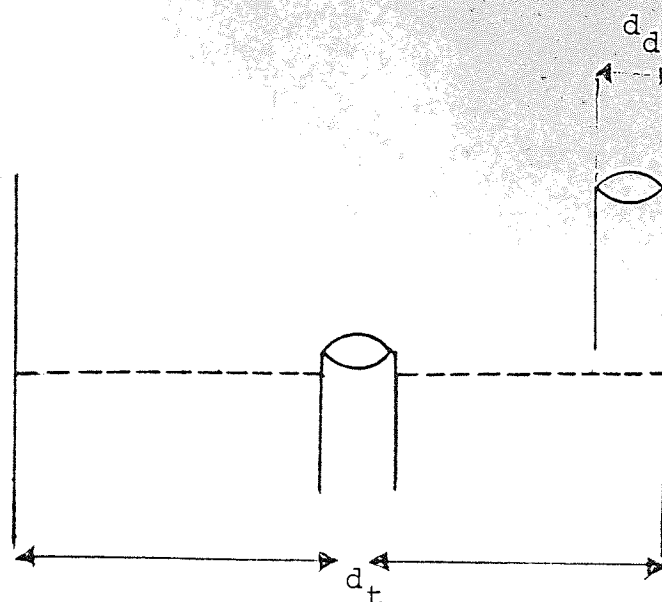


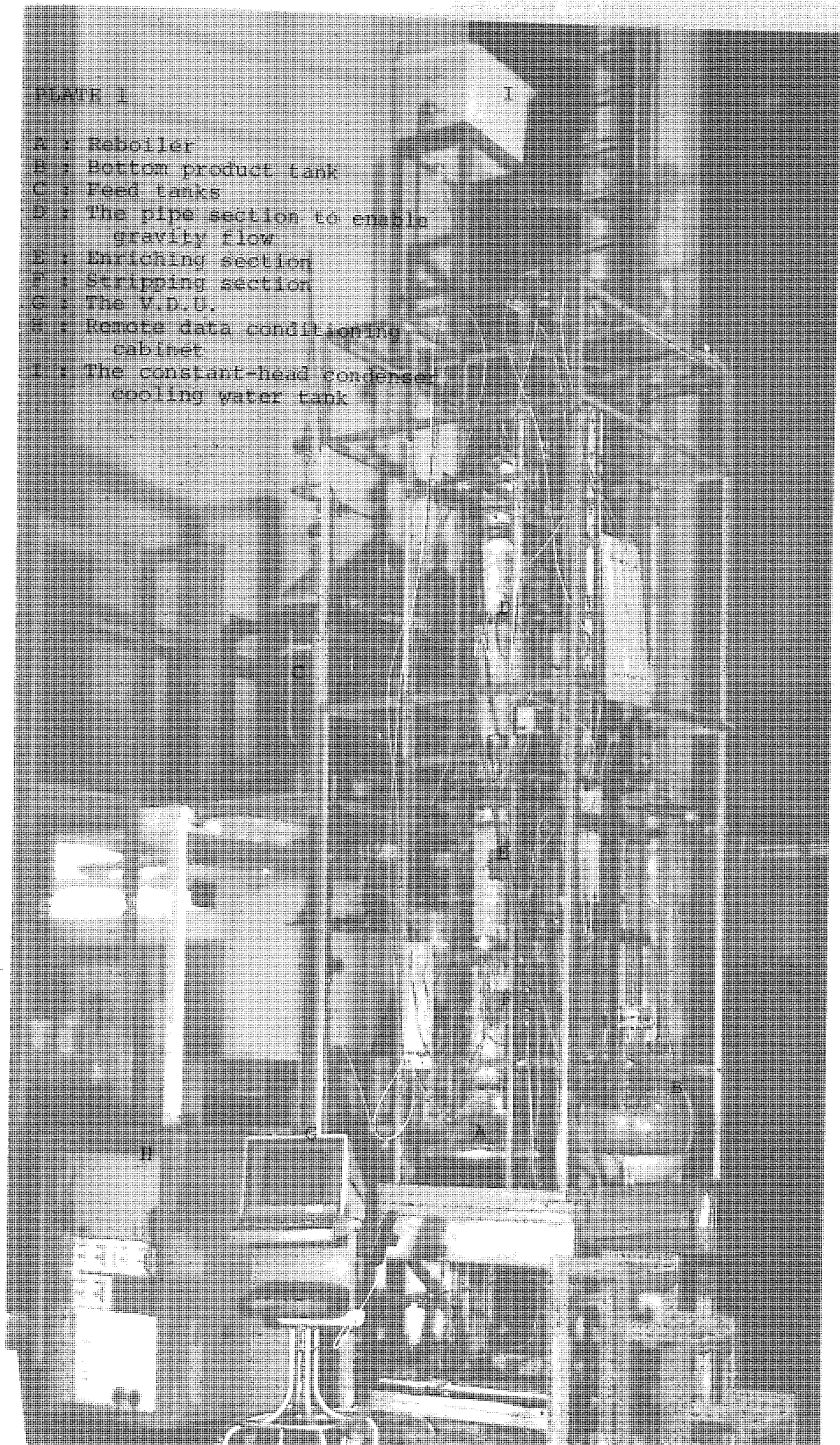
Figure III.3 - The Schematic Diagram of a Sive Tray in the Column

Diameter of the Tray	0.762 m
Diameter of the Downcomer	0.105 m
Tray Thickness	0.002 m
Diameter of the Perforations	0.0011 m
Number of Perforations	145 holes per tray
The Weir Height	0.003 m

Table III.2 - The Characteristic Dimensions of a Tray and Other Geometrical Information

PLATE 1

- A : Reboiler
- B : Bottom product tank
- C : Feed tanks
- D : The pipe section to enable gravity flow
- E : Enriching section
- F : Stripping section
- G : The V.D.U.
- H : Remote data conditioning cabinet
- I : The constant-head condenser cooling water tank





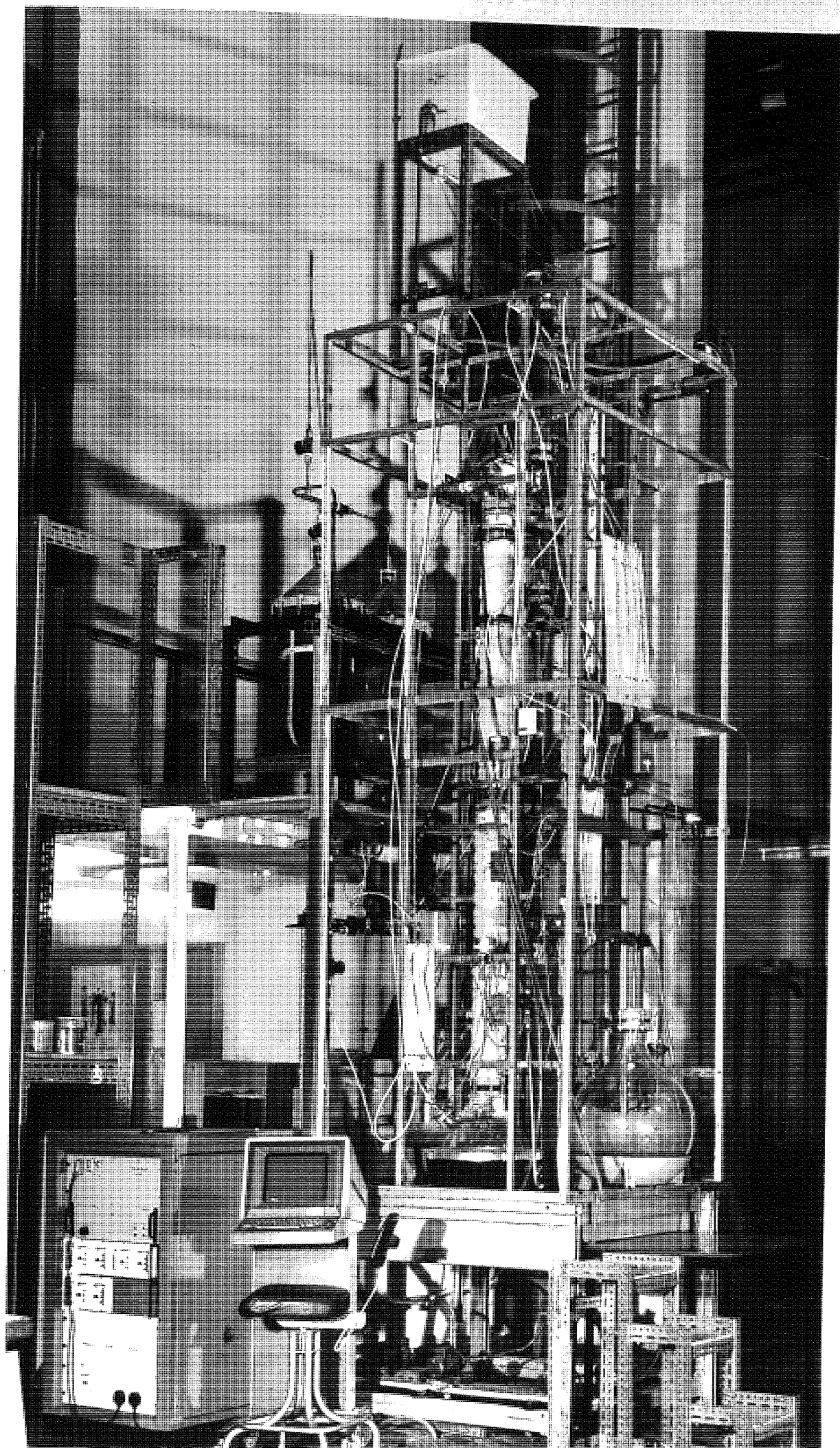
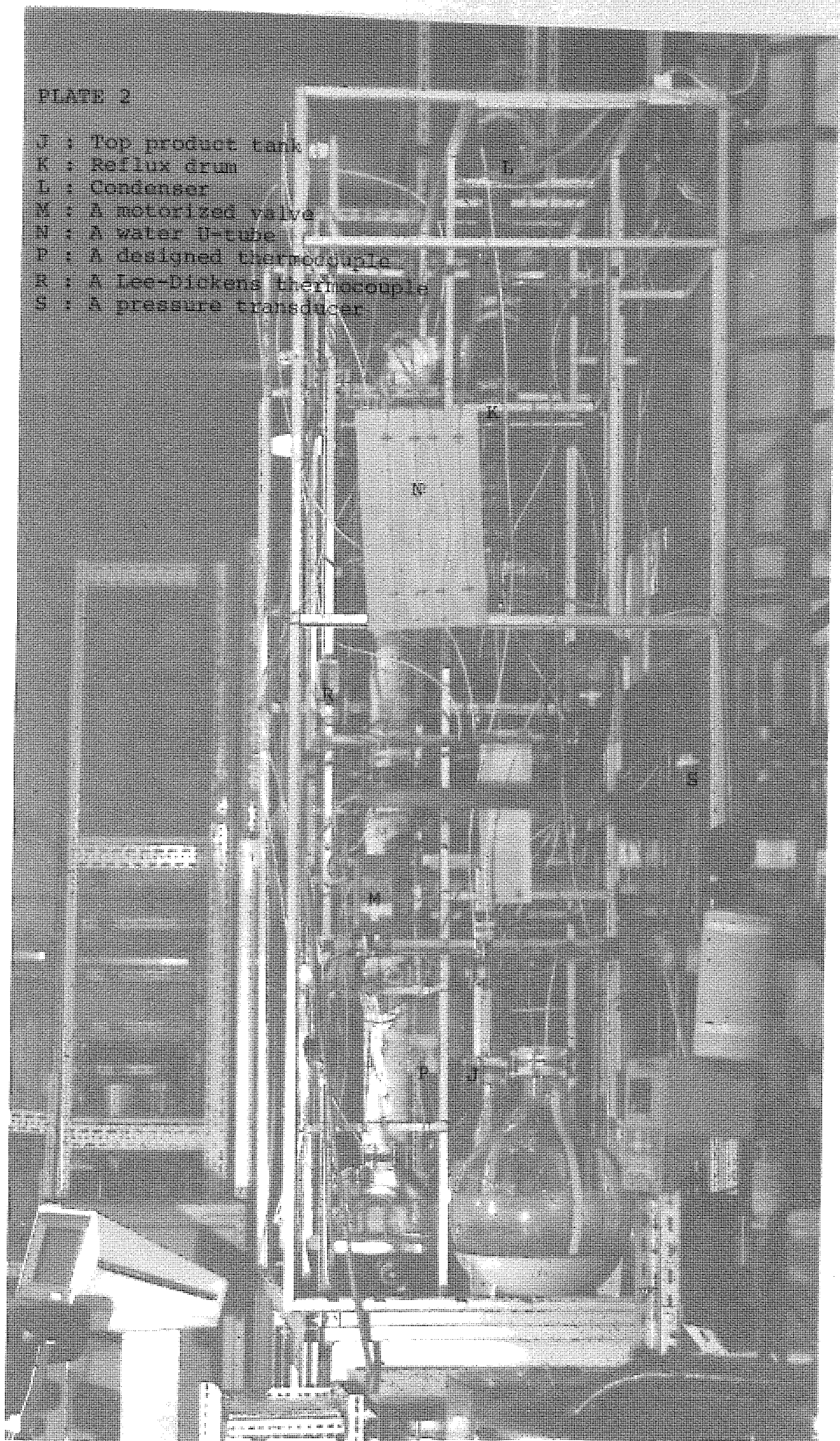




PLATE 2

- J : Top product tank
- K : Reflux drum
- L : Condenser
- M : A motorized valve
- N : A water D-tube
- P : A designed thermocouple
- R : A Lee-Dickens thermocouple
- S : A pressure transducer





A black and white photograph of a large, complex scientific apparatus, likely a particle detector or accelerator component, housed within a tall metal frame. The apparatus features a large, rounded, metallic structure at the bottom, possibly a cryostat or target chamber, and is surrounded by various pipes, cables, and structural supports. The background shows a laboratory setting with shelving units.



PLATE 3

- A : Sockets for the 8316 Peripherals
- B : 8316 sense switches
- C : Visual displays of the input driving voltages for the six analogue output channels and the switches for manual operation
- D : Bottoms pump switch
- E : The feed recycle pump switch
- F : The reboiler mains switch
- G : The master switch
- I : The feed pump switch

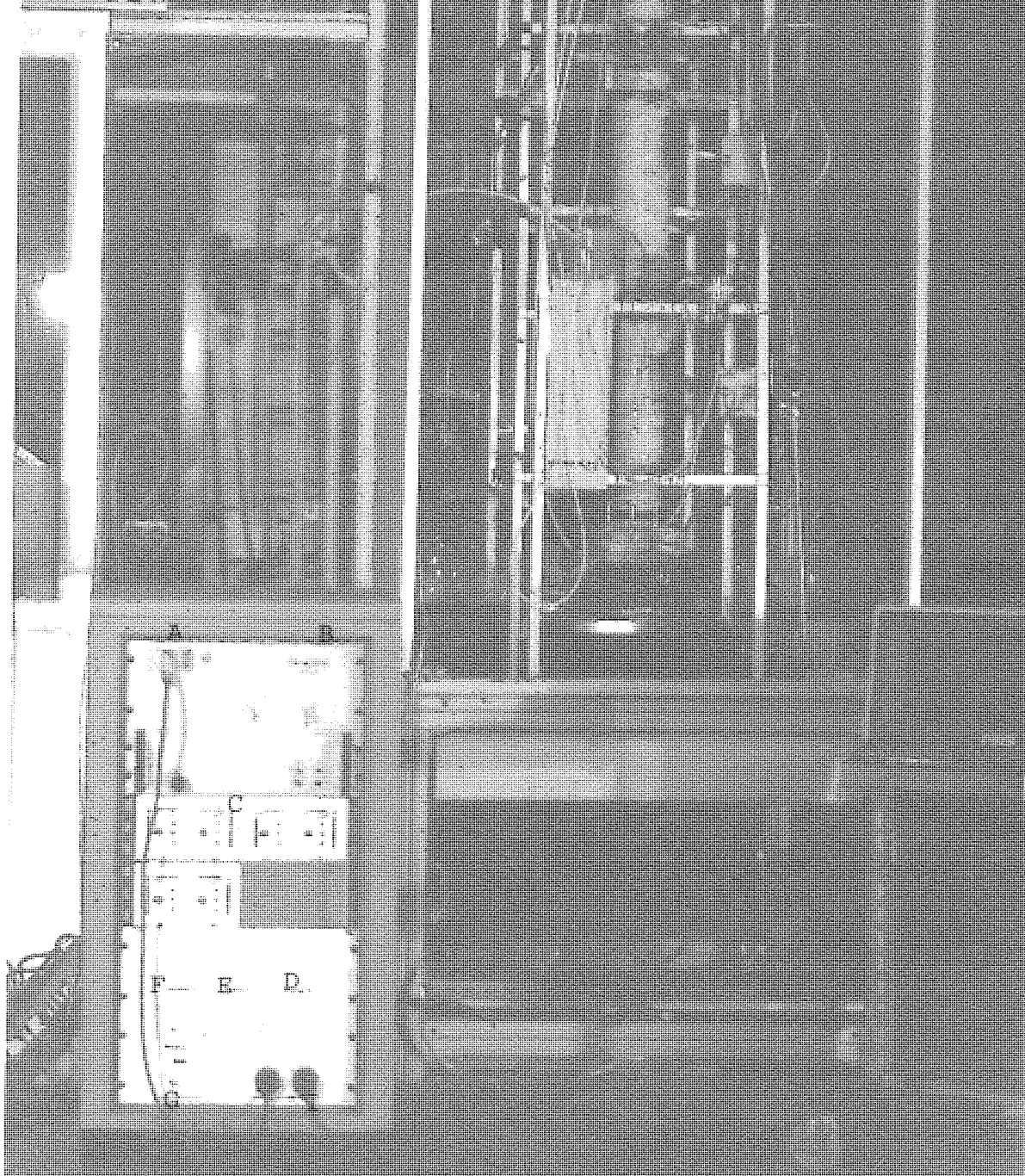
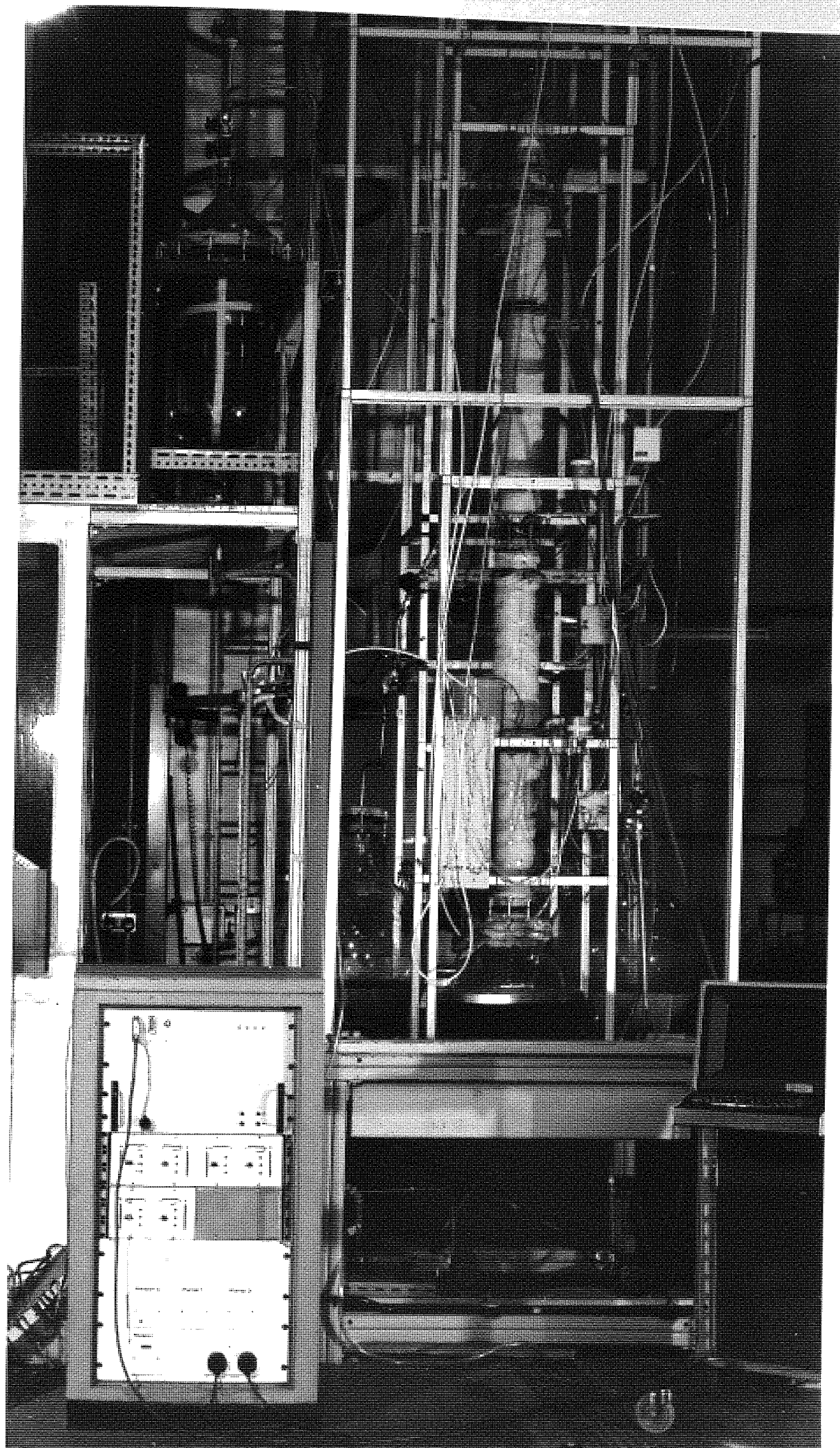




PLATE  
A: 2  
B: 4  
C: 7

D: 1  
E: 1  
F: 1  
G: 1  
I: 1



### III.1.2 THE MOTORIZED VALVES

Liquid flow control by electric signal is done by an instrument known as Lek-Set which converts an electric signal into the mechanical adjustment of a flow control valve so that a desired liquid flow rate results from a specific input.

A software package known as the HADIOS Executive is available which enables analogue signals to be transmitted from the computer to the valves. Detailed discussion of HADIOS and its associated software will be given in due course in this Chapter and also in Chapter V.

The valves as presently installed on the column can, therefore, be driven automatically by a signal from the computer and, also, manually by pressing the appropriate switches on the panel of the remote signal conditioning unit positioned next to the distillation column (see the description of the interfacing of the column to H316 computer). Visual displays of approximate valve input signals have also been installed.

The response and shut-off characteristics of the valves were investigated by Daie (134) by side-bench experiments during which the valves were interfaced to the H316 computer individually and their characteristics were studied.

The shut-off characteristics of the valves can be modified to some extent by varying the length of

the valve needles, but complete shut-off is difficult to achieve. Therefore, each motorized valves is preceded by a manual valve to enable shut-off if need be.

The range of the input signals to the valve is 0 to 10 v. from fully closed to fully open stem positions. Their calibrations can be done insitu by outputting a signal from the computer and measuring the volumetric flowrate by stopwatch-and-bucket method. The output signal can then be correlated to the flow rate by the least squares method. The general form of the correlations is:

$$\text{output voltage} = g(\text{volumetric flow rate}) \dots \text{III.1}$$

The order of the polynomial fit for each valve was increased until the variance about the regression plane was almost invariant with the increasing order of the polynomial. These calibrations were found to be reproducible provided no electrical or mechanical adjustments were made to the valves.

Table III.3 provides the coefficients of the equations describing the motorized valves while their characteristic curves are given in Appendix A.1.

Valve	$a_i$	$b_i$	$c_i$	$d_i$	$e_i$	$\alpha_i$
Reflux	-0.08062	2.837	54.170	137.8	-	.998312
Bottoms	-0.843	14.9	-3.45	-	-	.989165
Feed	-0.04539	8.378	-2.732	-4.816	5.910	.996142
Distillate	0.405	49.2	-17.6	-	-	.988967

Table III.3 - The flow rates are in litres/min. and the voltages are in volts.  $\alpha$  is the correlation coefficient and  $a_i \dots e_i$  are the coefficients of the polynomials

## Valve Operation Problems

The following types of stiction can occur during the operation of the motorized valves:

- (i) electrical stiction; where the valves may literally not respond to changes in the input voltage of less than 1 volt
- (ii) mechanical stiction; where the mechanical parts of the valves may stick because of dirt and lack of lubrication

The first of these problems can be overcome by programming a "kick" to be sent to the valves every time their settings are changed or refreshed. This effectively means that the valves are driven towards their maximum opening to shift them slightly and, then, reset to their desired opening immediately afterwards. In programming language, this can be accomplished by two consecutive CALLS to subroutine 5 in the latest version of HADIOS Executive.

The mechanical problems can only be reduced by constant lubrication and maintenance.

The hysteresis effects were found to be minimal over an operation time of two hours.



### III.1.3 THE REBOILER

The reboiler is essentially a 2.4 kW, double circuit isomantle electric heater which can be driven by a maximum of 10 volts input voltage from the computer or manually.

The reboiler characteristics were studied insitu and it was found that for a certain input driving voltage, and a known mass of liquid, the temperature of the liquid rose linearly with time. This meant that the amount of heat transferred to the liquid, as calculated from equation III.2, could be conveniently correlated to the input signal.

$$Q = MC_p \frac{dT}{dt} \dots\dots\dots \text{III.2}$$

where

M = mass of the liquid in the reboiler

C<sub>p</sub> = specific heat capacity of the liquid

Q = the rate of heat transfer

and  $\frac{dT}{dt}$  is determined from the plot of temperature vs time

The experimental arrangement was as follows:

- (i) a variable speed electric stirrer introduced into the reboiler through the available spouts on the reboiler
- (ii) a precalibrated electric thermocouple
- (iii) a stopwatch

The mass of water as the liquid used for calibration was chosen to be 12 kg. because it happened to have the optimum volume needed to cover the entire surface area between the electric coil and the spherical glass container.

This experiment was repeated for different input voltages and Q was calculated from equation III.2 for each experiment. It was, therefore, possible to correlate the input voltage to the amount of heat transferred as

$$\text{The amount of heat transferred} = g(\text{input voltage})$$

$$\dots\dots\dots \text{III.3}$$

or

$$Q = .3312 - 0.1772V + 0.07919V^2 - 0.005239V^3$$

where

Q = the heat transferred      kj./sec.

V = input voltage                  volts

or alternatively

$$\text{Input voltage} = f(\text{the amount of heat to be transferred})$$

$$\dots\dots\dots \text{III.4}$$

$$V = 3.62 - 3.86Q + 6.59Q^2$$

As stated, during the calibrations the mass of the liquid was fixed at a level such that maximum heat transfer area was obtained. In actuality, the mass of liquid in the reboiler and thus the associated heat transfer area change during operation. Therefore, the heat transferred as calculated from equations III.3 and III.4 must be corrected for the variations in the heat transfer area. This correction factor

was obtained by fixing the input voltage to the reboiler and varying the mass of the liquid inside the reboiler and was found to be practically the same for any input voltage. Denoting this correction factor by R, it was correlated to the mass of the liquid contained by the following equations

$$R = g(\text{mass of liquid in the reboiler})$$

$$\text{or } R = -0.9183 + 0.4854M - 0.04422M^2 + 0.001914M^3 - 0.00004078M^4$$

..... III.5

where

$$R = \frac{Q_{12}}{Q_A}$$

$Q_{12}$  = heat transferred when the mass of liquid in the reboiler is equal to 12 kg. as calculated from equation III.3

$Q_A$  = the actual amount of heat transferred

The curve-fittings were done by the least squares method and the orders of the polynomials were increased until the variances about the regression plane were almost invariant with the increasing order of the polynomials.

The characteristics of the reboiler are given in Appendix A.2.



### III.2 PROCESS INSTRUMENTATION

Low-cost instrumentation was one of the side objectives of this research since expensive instrumentation often acts as a deterrent against computer control. Therefore, low cost measurement methods had to be devised in an attempt to achieve this objective and thus reduce the cost to an acceptable level. The approach to these developments was essentially teleological in that these developments were made to serve certain purposes. However, there is no reason why they cannot be duplicated and employed effectively elsewhere.

The present instrumentation of the distillation column will be discussed in following parts:

- (i) temperature measurement
- (ii) level measurement
- (iii) flow measurement

#### III.2.1 TEMPERATURE MEASUREMENTS

The Lee-Dickens Thermocouples:

These thermocouples were originally intended for plate temperature measurements on the column. Their calibrations, however, proved to be unduly cumbersome due to the fact that they were made up from very cheap and, thus, electrically primitive components such as low cost amplifiers and inherently drift-prone thermistors which constitute the automatic

zero compensation unit of the thermocouples.

At the outset, the scatter between consecutive readings amounted to  $\pm 12$  percent. The calibrations were further invalidated by the following observations:

- (i) the thermocouples gave different readings of the same nominal temperature
- (ii) they actually changed in different directions.  
In other words, one thermocouple showed a fall in the temperature of a water-bath while the others indicated a rise
- (iii) a ripple was observed in the output signal from the transducer when monitored on an oscilloscope
- (iv) there was a drift in the calibrations, i.e. consecutive calibrations showed different offsets

The non-uniformity in the readings of the thermocouples was found to be due to the pick-up of noise from various sources. The following sources of noise were identified.

- (i) the motorized valves are mains-operated and the interface between the mains and the driving signal from the Honeywell 316 was giving rise to a significant amount of noise which was readily being picked up by the thermocouples
- (ii) there was high frequency digital noise from the Honeywell 316 computer which affected the transducers

- (iii) there was noise pick-up from the internal power supply of the thermocouples.

These problems were further compounded by the fact that the impedances between the input to and output from the HADIOS were not properly matched and this, in turn, gave rise to additional inconsistencies in the calibration of the thermocouples.

The following remedies were conceived and implemented.

- (i) the noise originating from the motorized valves was minimized by the installation of an external power supply solely for the thermocouples.  
This proved to be effective as it reduced the valve interference and the resulting noise considerably
- (ii) the digital noise problem was overcome by the addition of a capacitor between the output from the H316 and input to the HADIOS
- (iii) the impedances between the input to and the output from the HADIOS were matched by adding an amplifier between the output from the thermocouples and input to the HADIOS
- (iv) the effect of transients caused by the internal power supply were alleviated by the following methods:
  - (a) the addition of a capacitor between the output from the thermocouples and the input to the HADIOS

(b) shortening the thermocouples as far as possible

(c) screening the thermocouples

Two lines of attack were available to overcome the problem of the ripple observed in the output signal from the thermocouples. These were:

(i) by more hardware modification involving the addition of a capacitor (integrator) to the feedback loop of the transducers

(ii) by a software modification to the HADIOS

Executive such that the ripple would be averaged out over a period of time

The notion of further hardware modification was abandoned because the integration of the ripple by a capacitor meant that any faults in the thermocouples such as the drifts of the automatic zero compensation unit would also be integrated.

It was therefore decided to add a piece of software to the latest version of the HADIOS Executive MOD.2, to enable the ripple to be smoothed out by taking as many equally-spaced samples as possible during the entire scan interval - the details of which will be discussed in Chapter V.

Finally the problem of drift in the automatic zero compensation thermistor can be overcome by bypassing the thermistor and using the melting point of ice as the reference temperature.

The result of these modifications was to eliminate non-uniformities and enable the calibration to be

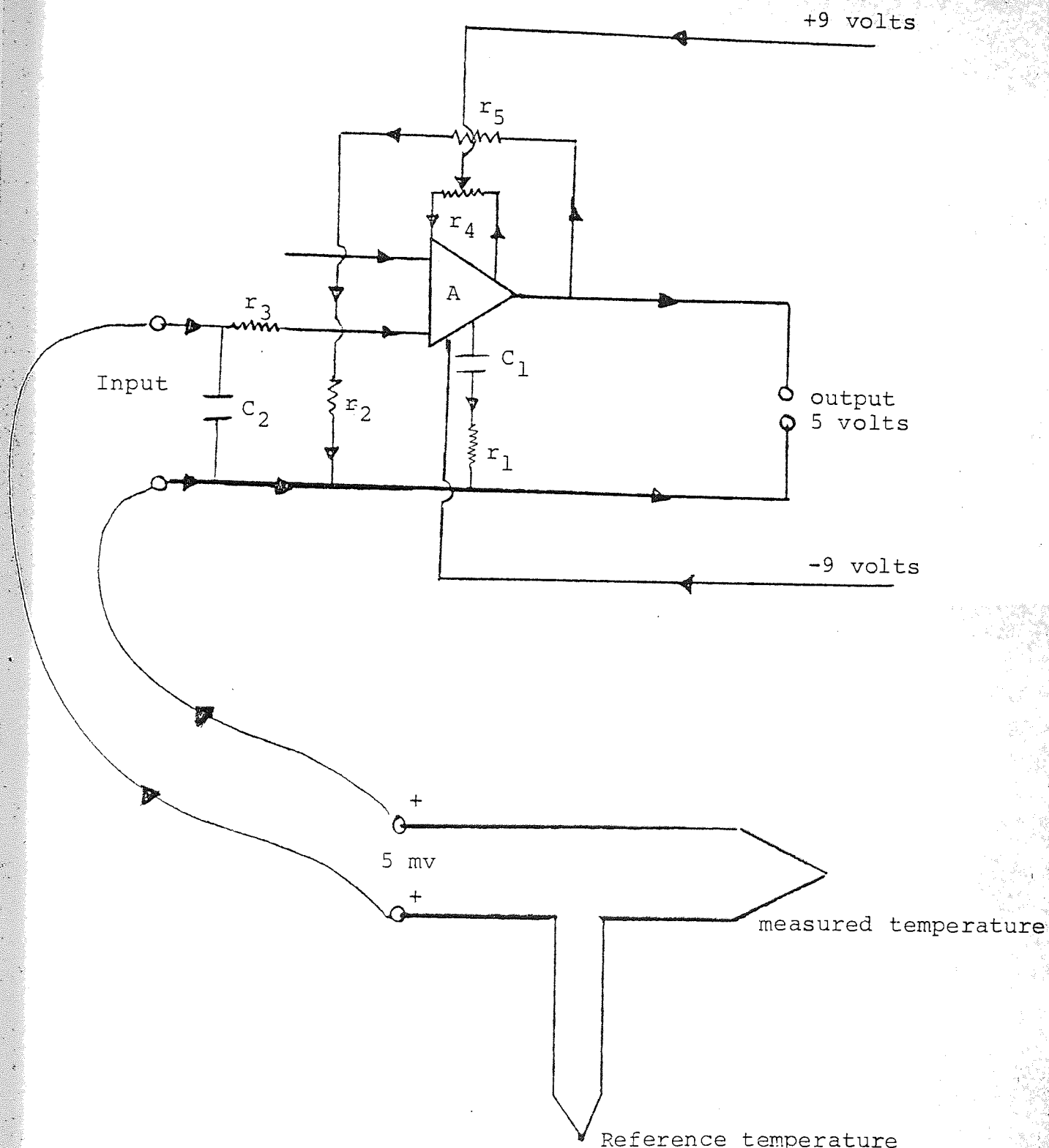
reproducible with an accuracy  $\pm 1^{\circ}\text{C}$ . This, however, was thought to be too inaccurate for tray temperature measurements and thus it was decided to use these thermocouples for the feed and reflux stream temperature measurements where the accuracy is not so crucial for open-loop experiments or control.

For tray temperature measurements, nonetheless, it is possible to get good accuracy and almost noise-free readings economically by the design proposed in Figure III.4, which has the following features:

- (i) nickel-chromium aluminium thermocouples
- (ii) high performance operational amplifiers known by the type number 725CN supplied by many manufacturers
- (iii) long-life batteries used as internal power supply
- (iv) the melting point of ice as the reference temperature
- (v) high capacitance capacitors of  $2000\ \mu\text{F}$
- (vi) a number of resistors chosen such that a gain of 1000 is obtained on the amplifier

These thermocouples have shown excellent reproducibility in calibrations with an accuracy of  $\pm 0.1^{\circ}\text{C}$  which is comparable to the expensive zero-chamber thermocouples that are recommended for such purposes.

The characteristic equations were obtained by correlating the measured temperature to the output signal and have been tabulated in Table III.4.



#### Notation

- A: high performance operational amplifier type 725CN  
 $C_i$ : capacitors each with a capacitance of 2000  $\mu\text{F}$   
 $r_i$ : resistances arranged such that the gain of 1000 is obtained on the amplifier

Figure III.4 - The Proposed Design for the Thermocouples

The characteristic curves are presented in Appendix A.3.

Thermocouple	$a_i$	$b_i$	$\alpha_i$
top tray	3.81021	23.0901	.998216
feed tray	3.95769	23.0626	.9899312
bottom tray	3.63583	23.0572	.996743
feed stream	-0.307	22.1	.981326
reflux stream	4.16	20.5	.973182

Table III.4

The form of the correlations is

$$T = a + bv \dots\dots\dots \text{III.6}$$

where

$T$  = temperature  $^{\circ}\text{C}$ .

$v$  = voltage volts

$\alpha$  = correlation coefficient

The curve-fittings were done by the least squares method.



### III.2.2 CONTINUOUS LEVEL MEASUREMENT

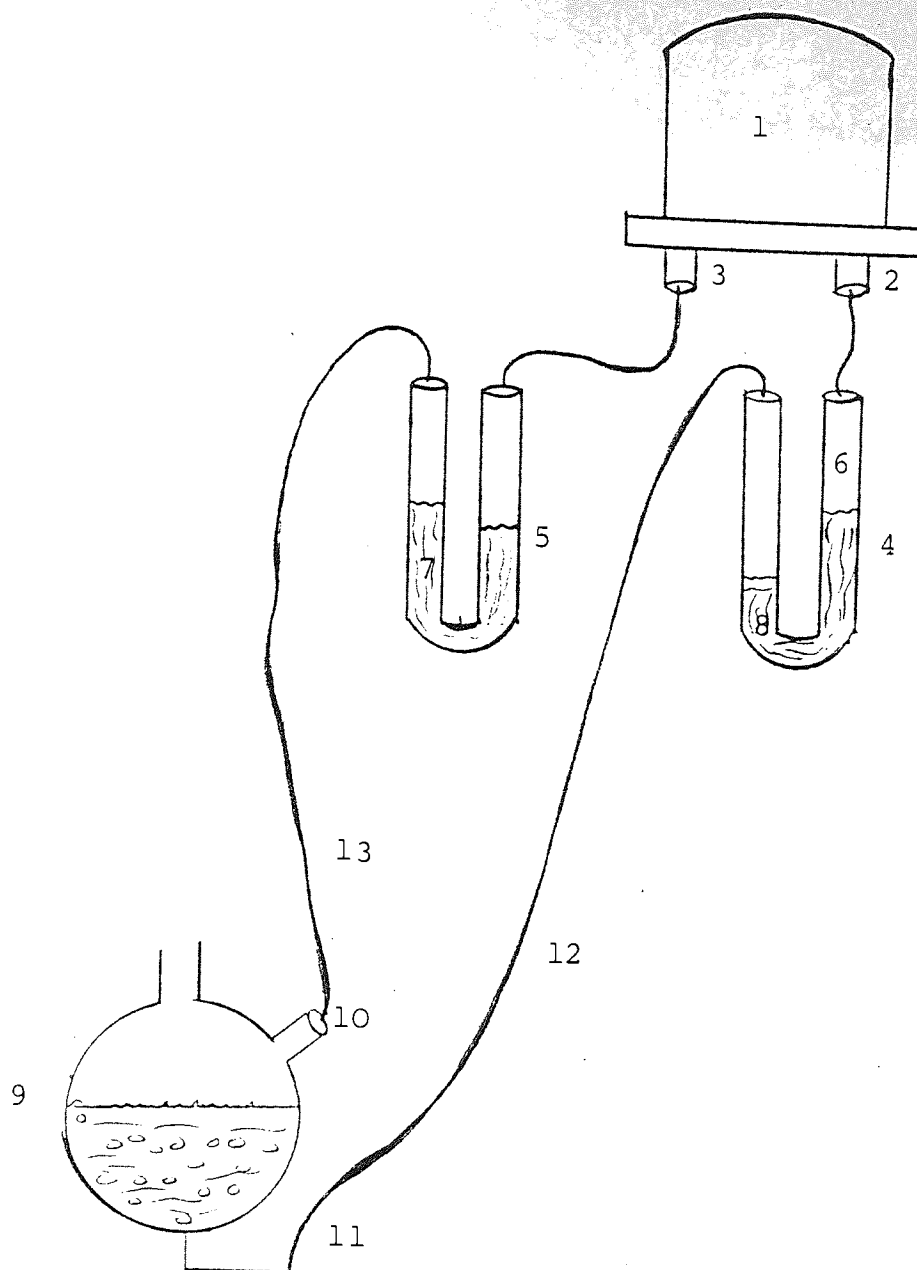
The air differential pressure transducers supplied by the IBM can be used to monitor the liquid level in a vessel provided that they are isolated from the liquid by an air-lock, as demonstrated by Daie (134), in order to avoid corrosion. With such an arrangement the response of the transducer to changes of pressure, induced by the level changes in the vessel, is linear. This means that the holdup of liquid in the vessel can be correlated to the transducer output as

$$\text{Holdup} = g(\text{output voltage}) \dots\dots\dots \text{III.7}$$

The two level measurements needed for the column operation are made at the reboiler and the reflux drum. The arrangement for the reboiler is shown in Figure III.5. The arrangement for the reflux drum is similar.

The calibration and the filling-up procedures are as follow:

- (i) empty the reboiler
- (ii) disconnect the transducer connections at the transducer
- (iii) place sufficient liquid in the reboiler so as to cover the dead zone in the reboiler. This can be judged visually and normally needs approximately 200 cc. of liquid
- (iv) connect the upper transducer connections
- (v) fill up the reboiler (in stages with known



- 1 : the air pressure transducer
- 2 : the high pressure connection
- 3 : the low pressure connection
- 4&5: the u-tubes
- 6 : the air-lock
- 7&8: water as the liquid in the u-tubes
- 9 : the reboiler
- 10&11: lower transducer connections; pressure measurement points
- 12&13:  $\frac{1}{4}$  inch P.T.F.E. tubing

Figure III.5 - The Arrangement for the Liquid-Level Measurement in the Reboiler

masses of liquid if it is being calibrated and record the transducer reading)

The calibration of the reflux drum is simply done by inserting known masses of liquid in the drum in stages and recording the transducer output.

The calibrations are reproducible provided that the above filling-up procedure is observed. The equations describing the level indicators are:

The reboiler:  $M_B = -32.9 + 23.8 V \dots\dots\dots \text{III.8}$

The reflux drum:  $M_{RD} = -0.326 + 0.513 V \dots\dots\dots \text{III.9}$

where the holdup (M) is in kg. and the transducer reading (v) is in volts. The curve fittings were done by the least squares method.

The characteristics of the level indicators are given in Appendix A.4.

### III.2.3 FLOW MEASUREMENT

In addition to measuring the flow rate by correlating it to the valve opening, a second method could be by a similar arrangement to that of level measurement. The only difference is that the differential pressure is induced by an orifice plate instead of a difference in the liquid level. The flow rate can then be correlated to the transducer output.

The accuracy of the flow measurement by this method was found to be  $\pm 50$  cc./min. Although this level of accuracy may be tolerable at flow rates greater than 500 cc./min., this arrangement can be somewhat problematical at low flow rates. Due to the limitations of the maximum heat load on the reboiler, the maximum flow rate during operation had to be confined to 150 cc./min. which effectively ruled out the measurement by this method and it was not used in this research.

Nonetheless, for completeness, the calibration equations for these arrangements are given in Appendix A.4.

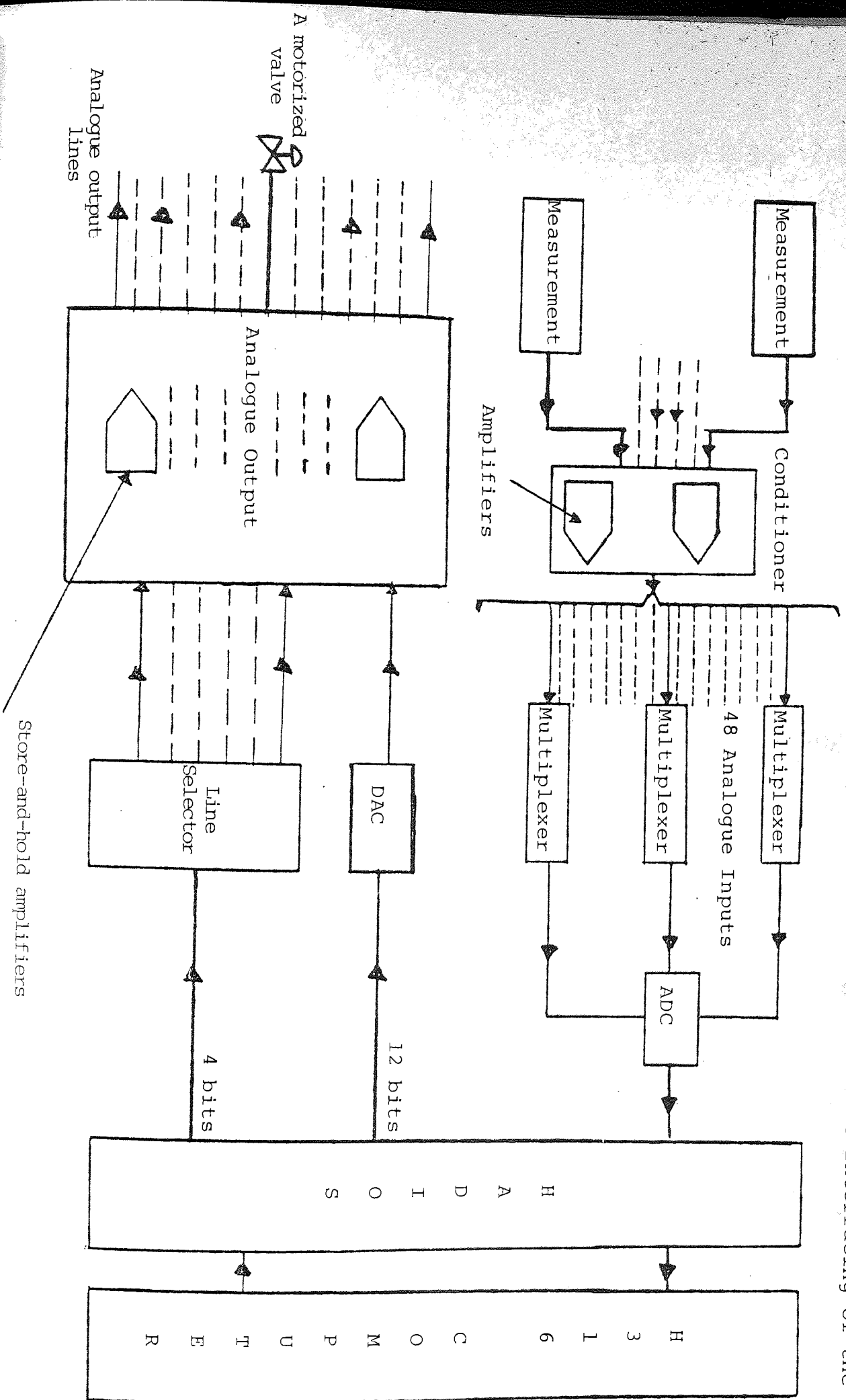
### III.3 THE INTERFACING OF THE COLUMN TO THE HONEYWELL 316 COMPUTER

The hardware involved in the interfacing of the column to the Honeywell 316 computer is depicted schematically in Figure III.6. A total of 12 analogue inputs and six digital outputs are used, for data acquisition and control, on the column as it stands at present.

On the available departmental facilities, a single channel ADC is used to handle 48 analogue input channels by three multiplexers. The operation involves completing the conversion of one input, resetting the circuit and applying a new input to the converter. Thus a maximum of 48 separate analogue signals can be processed in turn by the ADC, the input signals (0 to 5v) being converted to a binary integer with a 10 bit resolution, i.e.  $0 \text{ to } 1023_{10}$ . The output devices needed for the transmission of information from the computer are mainly application dependent. As regards the distillation column this essentially comprises a line selector, a DAC and an analogue output device which comprises a series of store-and-hold amplifiers. The resolution of the DAC is 12 bits which corresponds to 0 to 10 volts.

HADIOS provides a very flexible method of interfacing the Honeywell 316 computer to a wide range input/output devices for on-line applications. It basically consists of a controller, connected to the

Figure III.6 - The Schematic Diagram of the Hardware Involved in the Interfacing of the Column





computers input/output data and control lines, which generates subsidiary data, addresses and controls for up to 15 different subinterfaces. The operation of these subinterfaces is achieved by the output of control signals (initiated by programmable command) from the computer to the HADIOS controller which then carries out the majority of address and function decoding before initiating the required function of the requested subinterface. The system also has the ability to operate under interrupt control. This kind of operation is governed by the interrupt mask circuits of the HADIOS controller which can be set by the execution of programmable commands. The details of the programmable instructions used to operate HADIOS are given in the HADIOS manuals and also by Webb (27).

The modularity of construction of HADIOS allows systems to be simply configured to meet the particular requirements of each application. At present, the following facilities are available:

- (i) 48 analogue inputs
- (ii) three counters
- (iii) two digital inputs
- (iv) two digital outputs

Of these, only the digital outputs and analogue inputs have been employed to communicate with the present instrumentation on the column. The allocated analogue and digital channels are identified with the instrumentation on the column below in Tables III.5

and III.6 respectively.

Analogue Channel Number	Location and Function
36	Lowermost tray; thermocouple
37	Topmost tray; thermocouple
38	Feed tray; thermocouple
39	Feed flow; pressure transducer
40	Bottoms flow; pressure transducer
41	Distillate flow; pressure transducer
42	Reflux flow; pressure transducer
43	Condenser cooling water; pressure transducer
44	Reboiler LI; pressure transducer
45	Reflux drum LI; pressure transducer
46	Reflux stream; thermocouple
47	Feed stream; thermocouple

Table III.5 - The Analogue Input Channels

Digital Output Channel Number	Location and Function
A1	Reflux stream; motorized valve
A2	Bottoms; motorized valve
A3	Feed stream; motorized valve
A4	Distillate stream; motorized valve
A5	Condenser cooling water; motorized valve
A6	Reboiler

Table III.6 - The Digital Output Channels

## REMOTE DATA CONDITIONING

In order to convert the signals produced by the various measuring instruments into a form compatible with HADIOS and also the signal from the computer into a form acceptable to the various electrically operated devices on the column such as the motorized valves a remote signal conditioning unit has been constructed by the departmental electricians. Within this cabinet, all the analogue signals are converted to voltages, where necessary, and then amplified into the range 0 to 5 volts D.C. Also contained in this cabinet are:

- (i) the line drivers for the transmission of digital signals
- (ii) the power supplies for the transducers, motorized valves and the reboiler
- (iii) the analogue output device
- (iii) the manual/automatic switches for the valves and the reboiler required to start up the column

This cabinet is situated adjacent to the distillation column both for convenience and also to minimize the effects of electrical noise during the transmission of signals to the computer.

### III.3.1 THE HONEYWELL-316 COMPUTER

The Honeywell-316 computer is designed for both batch scientific applications and real-time on-line data processing and control. The wide variety of applications which can be implemented include data acquisition, simulation, control and batch scientific computation.

These applications are undertaken using an instruction repertoire of seventy two commands, a memory cycle of 1.6  $\mu$ s and input-output data handling at a maximum rate of 156 KHZ/second. The computer is a stored program, parallel binary type using two's complement machine code. A single 10-bit address with indexing and indirect addressing accesses a 16-bit (5 octal digits plus the sign bit) coincident-current ferrite core memory; one hardware index register is provided. The memory is a random access system expandable from 4k to 32k words - the computer used in this research has a memory size of 16k words. Other features of the central processing unit (cpu) include a real time clock, high speed multiply/divide and a single interrupt line.

The general characteristics of the H316 computer are given in Table III.7. The H316 computer uses the DAP-16 symbolic assembly program language for translation of source programs to machine code. The other source program languages available to the user are FORTRAN and BASIC. The system also allows mixed-language programming.

## The Peripheral Equipment

Six peripheral devices are connected to the central I/O bus of the central processor which are as follows:

- (i) a high speed paper tape reader operating at 200 characters per second
- (ii) a high speed paper tape punch operating at 75 characters per second
- (iii) a magnetic tape cassette unit used for both input-output; input at 375 bytes per second and output at 375 bytes per second
- (iv) a teletype operating at 10 characters per second
- (v) a Textronix 4010-1 visual display units (VDU). .  
This VDU is capable of both graphical and character display and in the alphanumeric output mode operates at a rate of 200 baud. It is possible to use the VDU both in the computer room and adjacent to the distillation column. Attached to the VDU is a hard copy unit, which provides permanent copies of the display when required. The hard copy unit can be operated either by depressing a switch situated on the VDU or by programmed commands
- (vi) an AED 3100p floppy disc drive unit

Primary power	475 watts, 5.5 amps. at 115 vac ± 10% at 60 ± 2HZ
Type	parallel binary solid state
Addressing	single addressing with indexing and indirect addressing
Machine code	two's complement
Circuitry	integrated
Signal levels	active: 0 volts passive: +6 volts
Instruction complement	72 instructions
Speed, Add	3.2 $\mu$ s
Subtract	3.2 $\mu$ s
Multiply	8.8 $\mu$ s
Divide	17.6 $\mu$ s
Standard memory	designed to protect memory data in the event of primary power failure
Standard interrupt	single standard interrupt line
Input/output modes	single word transfer single word transfer with priority interrupts
Standard I/O lines	10-bit address bus (4 function code and 6 device address); 16 input bus; 16 output bus; priority interrupt, external control and sense lines
Standard teletype	read paper tape at 10 cps; punch paper tape at 10 cps; print at 10 cps, keyboard input; off-line paper tape preparation, reproduc- tion and listing
Environment	room ambient temperature: 0-45°C
Cooling	filtered forced air

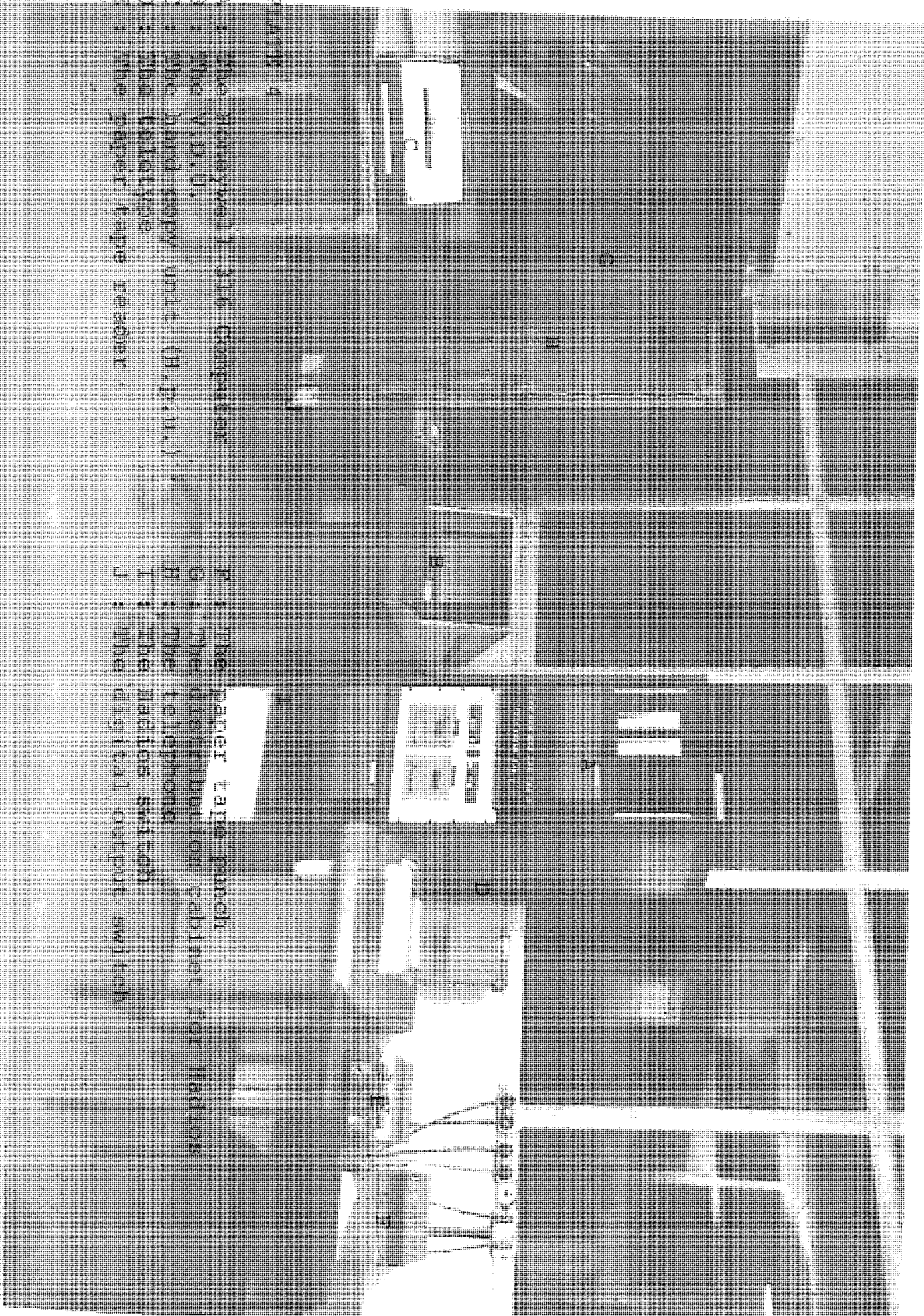
Table III.7 - Honeywell 316 Leading Characteristics



PLATE 4

A : The Honeywell 316 Computer  
 B : The V.M.U.  
 C : The hard copy unit (H.P.U.)  
 D : The teletype  
 E : The paper tape reader

F : The paper tape punch  
 G : The distribution cabinet for radios  
 H : The telephone  
 I : The radios switch  
 J : The digital output switch



E : the paper tape reader  
D : the teletype  
C : the hard copy unit (H.P.U.)  
B : the V.D.U.  
A : the Honeywell

1 : the signal output switch  
H : the teletype switch  
G :





### III.4 PROCESS OPERATION

#### Start-up

The following procedure should be followed to start the column:

1. Switch the mains power on using the switch labelled MASTER on the cabinet next to the distillation columns.
2. Switch all the valves and the heater to manual mode of operation by depressing the buttons near the visual input voltage display dials.
3. Switch on
  - (i) the Honeywell-316 computer and load the HADIOS Executive MOD.2
  - (ii) the HADIOS : the switch labelled I on plate 4
  - (iii) the digital output switch in the HADIOS distribution cabinet: the switch labelled j on plate 4
4. Empty the reboiler.
5. Recycle the feed stock a couple of times to ensure good mixing of the components.
6. Disconnect all the transducer connections at the transducers to allow air into the transducers.
7. Ensure that all the valves are working and that there are no stiction problems by closing and opening them a couple of times using the manual operation switches.

8. Fill the reboiler up to the required level by the procedure laid out in section III.2.2.
9. Connect the transducers up and check that the air-locks and the u-tubes are intact in all flow and level measurement lines.
10. Turn on the cooling water for the condenser and the heat exchange in the bottom product line.
11. Switch the heater on and run the column at total reflux for at least 20 minutes to ensure that the trays are filled (the reflux valve fully opened).

Precaution: while operating under total reflux ensure that the manual valves preceding the feed and distillate motorized valves are fully closed.

12. Switch the feed pump on and open the feed valve gradually to allow the feed into the column.
13. Set the reflux valve to the right opening.
14. Switch the thermocouples on and switch to automatic mode of operation and let the computer take over.

The column takes approximately 30 minutes to reach steady state after which disturbances can be introduced and experimentation can begin.

#### Shut-down

The following shut-down procedure needs to be followed:

1. Switch the heater off.
2. Switch all pumps off.
3. Turn all the manual and motorized valves off.

4. Switch the thermocouples off.
5. Switch off the HADIOS, the H316 computer and all its associated peripherals.
6. Switch the master-switch off:
7. Allow the column to cool down for at least 30 minutes and turn off the cooling water taps.

CHAPTER FOUR  
DYNAMIC SIMULATION



#### IV.1 DYNAMIC SIMULATION

As processes become more complex, incorporating ever-increasing degrees of automation, there will be a greater need for the analytical approach to the problems associated with their design and operation. Deterministic analysis of multivariable systems usually involves some form of mathematical modelling which has long been a favoured preliminary to a commercial plant as far as chemical engineers are concerned. There are various mathematical models for the same system, each one suited to solve a particular problem associated with the system. Two broad classifications constitute steady-state and dynamic models, that are used for steady-state and dynamic simulations respectively.

As regards dynamic simulation, the amount of detail that needs to be included in the model is usually determined by the purpose that the dynamic simulator is to serve. For instance, a dynamic model intended for control studies may need a lesser degree of sophistication than the one geared to design and safety studies. Of interest to this thesis is the application of dynamic simulation for control studies using a digital computer and this largely governs the assumptions that are made to simplify the mathematical model of a binary distillation column to render it more practicable.

One important aspect of mathematical modelling is the arrangement of the equations. It is generally believed that if the equations are arranged in a logical

or cause-and-effect order, the computer model is stable. This sequence is normally termed as the "natural" order, for it invariably parallels the cause-and-effect sequence found in nature.

In order to avoid unnecessary duplication, "continuous digital dynamic simulation" will henceforth be referred to as simulation and, moreover, the discussion will be confined to "process simulation" using FORTRAN only.

In a simulation exercise, usually a structure is set up to encompass the mathematical model and to communicate with an integrator in order to solve the differential equations that form the mathematical model. Almost invariably the linear or non-linear differential and algebraic equations constituting the mathematical model of the system need to be solved simultaneously and thus the problem of the simultaneity of the equations must be treated with due care.

Another important issue in simulation is the problem of initialization which needs considerable care. The choice of initial conditions to solve the differential equations must be realistic and physically feasible. An unrealistic set of initial conditions can lead to divergence or a solution which, although mathematically possible, is physically nonsensical. Therefore, if physically meaningful solutions are sought, judicious choice of initial conditions is imperative.

The back-bones of a dynamic process simulator normally comprises:

- (i) a definite structure for communicating with an integrator
- (ii) a number of individual modules each made up from a collection of linear or non-linear algebraic and differential equations
- (iii) an integrator
- (iv) a channel for outputting information
- (v) a library of utility routines to perform various functions such as curve fitting, arbitrary function generation, solution of non-linear algebraic equations, etc., depending on the needs of the problem.

## IV.2 THE STRUCTURE OF A DYNAMIC SIMULATOR

In a dynamic process simulator next to the mathematical modelling aspects, the role of the structure relative to that of the integrator is of central importance and has considerable bearing on the flexibility of the simulator. Unfortunately, most, if not all, of the available integrators have been designed for "system" simulation and require that a structure be set up in a predefined manner to suit the integrator. The user is expected to formulate the mathematical model of the system which usually appears in the form of a subroutine that can be called by the integrator as necessary. In such structures, normally, once the integrator is called, it then takes full control of the simulation with little further user interference. In such a picture, the structure can be considered as being subordinate to the integrator. This arrangement can be somewhat limiting and cumbersome at "process" simulation level at which the simulator is, usually, expected to supply a library of individual simulator modules and the user is relieved of the mathematical modelling problems. Ideally, at process simulation level, one would like an integrator which can be called autonomously at any point within the structure to update any number of variables and report back to the structure at the end of any number of integration steps. Additionally, experience has shown that it is often helpful if the independent variable is advanced outside

the integrator as opposed to its being advanced by the integrator which is the common feature of the integrators intended for system simulation. This aspect can enhance the flexibility of the integrator, and hence that of the simulator, in the following ways:

- (i) it enables frequent step size and integration order manipulations to achieve superior computational efficiency
- (ii) it enables different control and estimation routines to be interlocked into the simulator with relatively more ease and without having to restructure the simulator modules
- (iii) in on-line application and when variable step integration methods are being used, the chances of missing a sample or a control point can easily be made zero with little programming effort.

In other words, the integrator is subordinate to almost any structure that may be fit for a certain problem. To bring this about, a collection of four FORTRAN subroutines, namely, SDINT, INTJS, INTPAS and PRINT are proposed. These will be henceforth referred to as the SDINT subroutines.

Experience with a wide range of typical chemical engineering problems has shown that, with almost no exception, the fourth-order Runge-Kutta method is quite adequate for any situation and that the second- and first-order methods will provide reasonable accuracy coupled with greater computational speed. The SDINT subroutines offer a choice of three different fixed

step integration methods which are as follows:

- (i) the Euler's method; a first order method
- (ii) the Euler's predictor-corrector method;  
a second order method
- (iii) the fourth-order Runge-Kutta method;  
a fourth order method

Due to the important role of the integrator in any dynamic simulation study some elaboration on the general arrangement of the main program and that of the individual simulator modules will be in order at this stage. The full documentation of the SDINT subroutines is given in Appendix B. A simple example of how the SDINT subroutines can be used to simulate a system is also given in Appendix B. The system chosen for illustration is described by a second order ordinary differential equation that is reduced to a set of two first order differential equations which must be solved simultaneously.

#### General Arrangement of the Main Program for the Use of the SDINT Subroutines

The main programme arrangement is depicted in Figure IV.1. Following a preliminary housekeeping section containing FORMATS and DECLARATION statements, the initialization section is laid out. Here all the calculations and specifications for the problem parameters and coefficients are made. These are the values that are normally invariant during the course of the



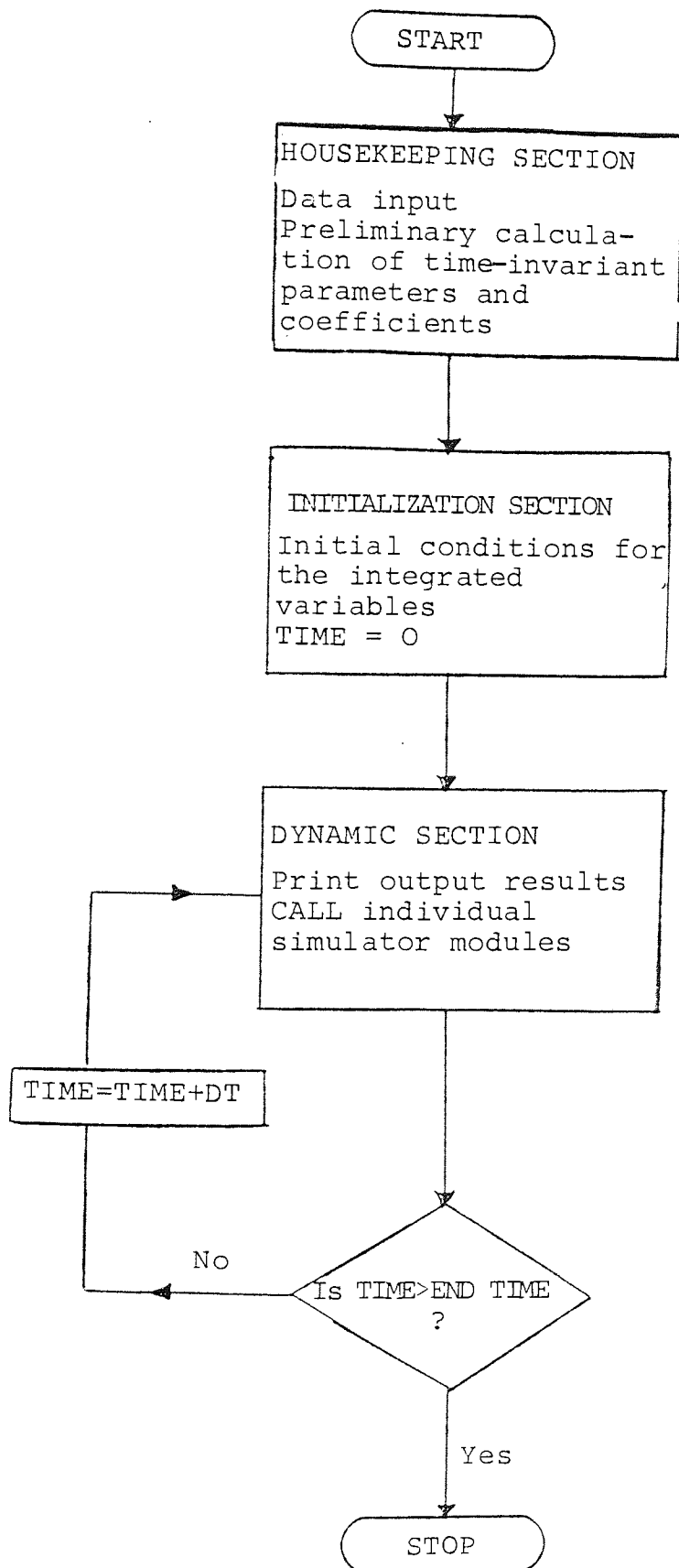


Figure IV.1 General Arrangement of the Main Program for the Use of SDINT Subroutines.  
DT Is the Integration Step Size.

calculations. In this section the initial conditions for the integrated variables must also be specified and the independent variable must be set to zero. The next section is the dynamic section in which the individual simulator modules are called to perform the simulation and the independent variable is advanced when all the modules have been updated.

#### The Program Arrangement for the Individual Simulator Modules

The individual simulator modules must be laid out according to the flowchart shown in Figure IV.2.

Each module essentially comprises:

- (i) the preliminary calculation section (if necessary)
- (ii) the derivative section in which the derivatives are computed
- (iii) the integration section where the integrated variables are updated
- (iv) the test for the step completion and a CALL to the subroutine INTPAS to zero the integrator pass numbers for the next integration step.

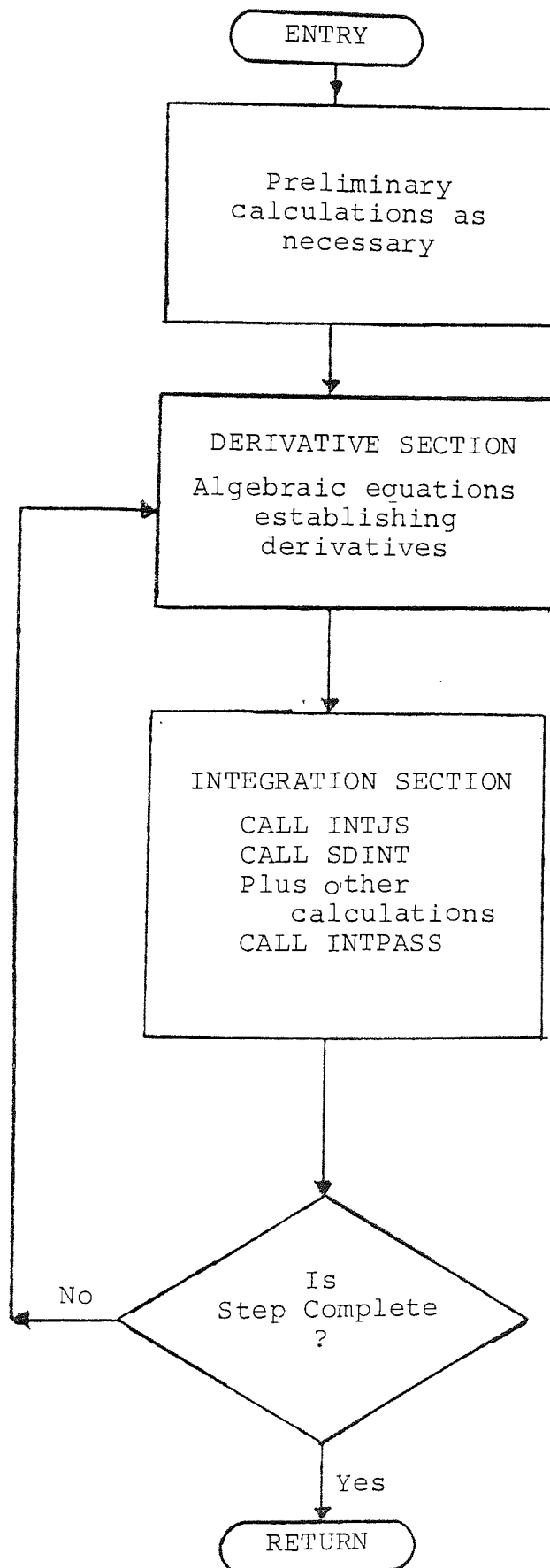


Figure IV.2 Subprogram Arrangement for a Simulator Module

### IV.3 MATHEMATICAL MODEL OF A DISTILLATION COLUMN

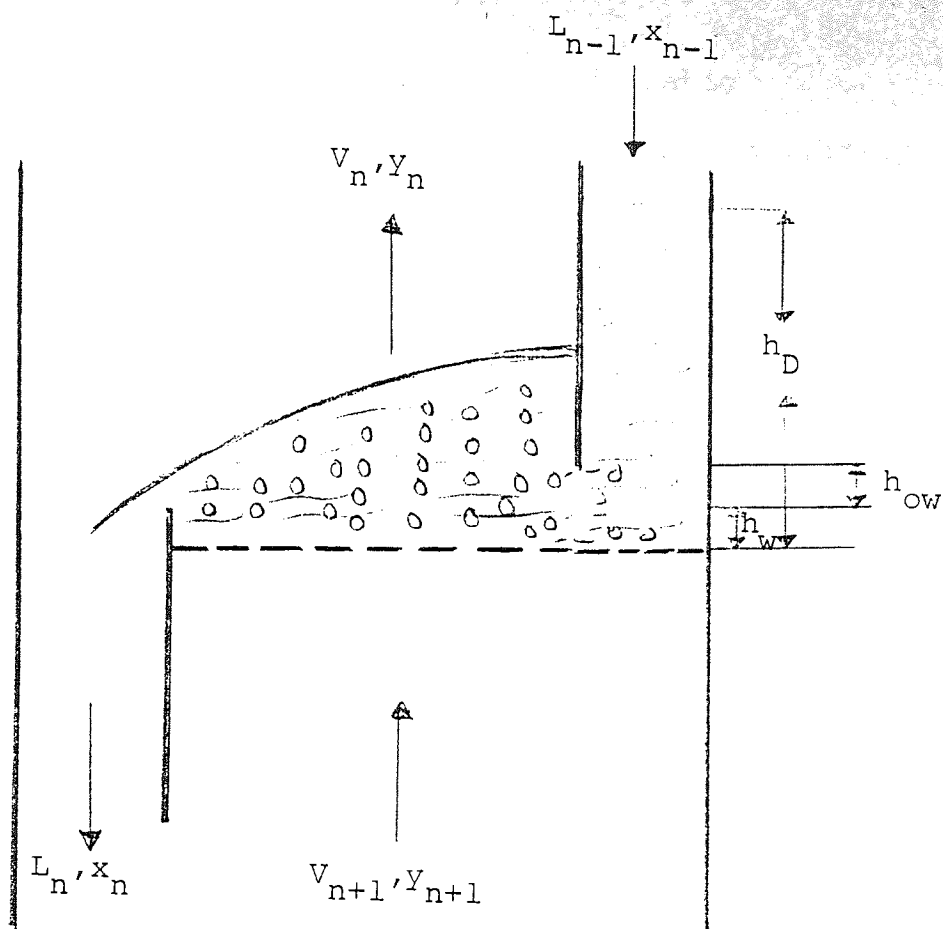
The model of a distillation column can be approximated by modelling a typical tray with ideal vapour-liquid equilibrium and stepping this up from a single tray to a column with a number of similar trays. The models of the column accessories such as the reboiler and the condenser can then be added to this picture to enable a complete mathematical description of the column. Further sophistications such as allowing for the non-ideality of the vapour-liquid equilibrium and real trays can then be introduced as necessary.

As indicated before, the perfectly mixed tray model is not only more flexible but also amenable to solution by digital computers and thus it will be adopted for the modelling of a tray in this thesis.

#### IV.3.1 THE MATHEMATICAL MODEL OF A TYPICAL TRAY

A typical tray is depicted in Figure IV.3. The assumptions that are made in its modelling are as follows:

1. Liquid on the tray is perfectly mixed and incompressible
2. The time constants for the fluid and thermal transfers are negligible compared with that for the mass transfer
3. Vapour hold-up is negligible compared with liquid hold-up



- $h_D$  = liquid height in the downcomer  
 $h_{ow}$  = liquid height over the weir  
 $h_w$  = height of the weir  
 $M_L$  = liquid hold-up  
 $L_n, V_n$  = liquid and vapour flow rates respectively

Figure IV.3 The Schematic Diagram of a Typical Tray

4. The column is essentially adiabatic
5. Vapour and liquid are in thermal equilibrium, i.e. at the same temperature, but not in phase equilibrium. A Murphree vapour-phase efficiency will be used to describe the departure from the equilibrium.

It is assumed that  $n$  denotes the plate number and  $j$  refers to the number of components.

- (i) total continuity equation : one per tray

$$\frac{d}{dt}(M_n) = (L_{n-1} + V_{n+1}) - (L_n + V_n) \dots\dots\dots \text{IV.1}$$

- (ii) component continuity equation :  $J-1$  per tray

$$\frac{d}{dt}(M_n x_n) = (L_{n-1} x_{n-1} + V_{n+1} y_{n+1}) - (L_n x_n + V_n y_n) \dots\dots\dots \text{IV.2}$$

- (iii) energy equation : one per tray

$$\frac{d}{dt}(M_n U_n) = (L_{n-1} h_{n-1} + V_{n+1} H_{n+1}) - (L_n h_n + V_n H_n) \dots\dots\dots \text{IV.3}$$

where

$M_n$  = molar liquid hold-up

$x_n$  = liquid composition on the  $n$ th tray (mole fraction)

$y_n$  = vapour composition on the  $n$ th tray (mole fraction)

$U_n$  = the internal energy (kJ/mol)

$h_n$  = liquid enthalpy (kJ/mol)

$L_n$  = liquid rate from the  $n$ th tray (mol/hr)

$V_n$  = vapour rate from the  $n$ th tray (mol/hr)



(iv) phase equilibrium : J per tray

$$y_n^* = g(f_n, x_n, T_n, \gamma_n) \dots\dots\dots \text{IV.4}$$

where

$y_n^*$  = vapour composition in equilibrium with  $x_n$

$f_n$  = fugacity (atm.)

$T_n$  = bubble point temperature °C.

$\gamma_n$  = activity coefficient

(v) fluid dynamic relationships:

(a) liquid; one per tray

with reference to Figure IV.3 we have:

$$M_{L,n} = f(h_w, h_{ow}, h_D, \text{hydraulic gradient across the tray, time}) \dots\dots \text{IV.5}$$

The exact relationship between liquid hold-up and liquid flow rate would be too complex if commonly used correlations for each liquid head term were evaluated. However, a commonly used expression is that of Brambilla (110) which is of the form:

$$M_{L,n} = A + BL_n + CF_n + Dh_w \dots\dots\dots \text{IV.6}$$

where

$F$  = vapour flow parameter =  
(vapour density)<sup>.5</sup>(vapour velocity)

A, B, C and D = constants available for different types of plates

(b) vapour; one per tray

$$V_n = f(P_n, P_{n+1}, Y_{n,j}, T_n) \dots\dots\dots \text{IV.7}$$

This equation is usually of the form

$$V_n^2 = \frac{P_{n+1} - P_n}{K_{DP} \cdot \zeta_n^V}$$

where  $\zeta_n^V$  is the vapour density on the nth tray  
and  $K_{DP}$  is the pressure-drop coefficient.

(vi) actual vapour composition equations; j per tray

$$Y_{n,j} = Y_{n+1,j} + E_{n,j} (Y_{n,j}^* - Y_{n+1,j}) \dots\dots \text{IV.8}$$

where  $E_{n,j}$  denotes the Murphree vapour-phase  
efficiency and \* denotes the equilibrium value.

(vii) thermal properties; two per plate

$$h_n = f(x_{n,j}, T_n) \dots\dots\dots \text{IV.9}$$

$$H_n = f(y_{n,j}, T_n, P_n)$$

#### IV.4 THE MODEL OF A BINARY DISTILLATION COLUMN

Most columns, in actuality, handle multicomponent feeds. But many can be approximated by binary or pseudo-binary mixtures. Therefore, binary distillation columns assume a very important position in the chemical plants. The objective here is to derive the mathematical model of a conventional binary distillation column with a total condenser and a reboiler and explore the possibility of making further simplifying assumptions to render the solution more practicable. The schematic diagram of the column is given in Figure IV.4.

##### IV.4.1 MODEL I

The purpose of studying this simplified case is to reduce the problem to its most elementary form so that the basic structure of the equations can be clearly seen. The following additional assumptions are made in the formulation of this model:

- (i) the feed and reflux streams enter the column as saturated liquids at their bubble points
- (ii) constant column pressure
- (iii) equimolal overflow, i.e.  $V_{n-1} = V_n = V_{n+1} = V$
- (iv) negligible time lags in the reboiler and condenser responses.

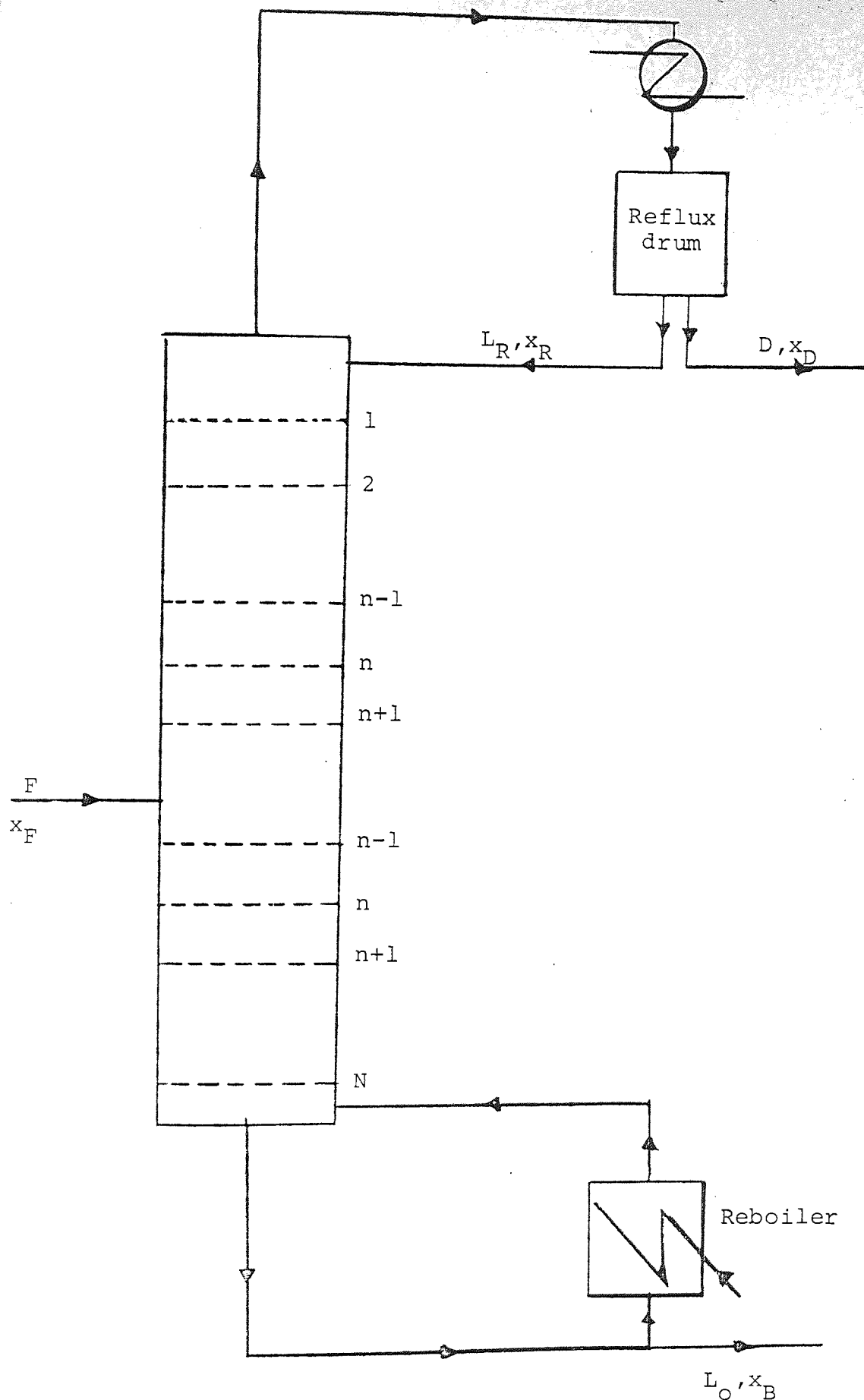


Figure IV.4 Schematic Diagram of a Conventional Distillation Column with a Total Condenser

(a) The Model of a Typical Tray

Total continuity:  $\frac{d}{dt} M_n = L_{n-1} - L_n \dots \text{IV.10}$

Component continuity:  $\frac{d}{dt} (M_n x_n) = L_{n-1} x_{n-1} + V y_{n+1}$   
 for the most volatile  
 $- L_n x_n - V y_n \dots \text{IV.11}$   
 component (M.V.C.)

Differentiating IV.11 and substituting for  $\frac{d}{dt} M_n$  from IV.10, equation IV.11 can be rearranged into the form

$$M_n \frac{d}{dt} x_n = L_{n-1} (x_{n-1} - x_n) + V (y_{n+1} - y_n) \dots \text{IV.12}$$

Fluid dynamic equation:  $L_n = \frac{M_n - A}{B} \dots \text{IV.13}$

Vapour-liquid equilibrium:  $y_n^* = f(x_n, T_n, P) \text{ IV.14}$   
 for the M.V.C.

Where  $P$  is the total column pressure and  $T_n$  is the bubble point temperature.

Actual vapour composition:  $y_n = y_{n+1} + E_n (y_n^* - y_{n+1})$   
 calculation  $\dots \text{IV.15}$

(b) The Model of the Feed Tray

Total continuity:  $\frac{d}{dt} M_n = L_{n-1} - L_n + F$   
 $\dots \text{IV.16}$

Component continuity:  $M_n \frac{d}{dt} x_n = L_{n-1} (x_{n-1} - x_n)$   
 for the M.V.C.  $+ V (y_{n+1} - y_n) + F (x_F - x_n)$   
 $\dots \text{IV.17}$

Fluid dynamic equation:  $L_n = \frac{M_n - A}{B}$   
 ..... IV.18

Vapour-liquid equilibrium:  $y_n^* = f(x_n, T_n, P)$   
 ..... IV.19

Actual vapour composition:  $y_n = y_{n+1} + E_n(y_n^* - y_{n+1})$   
 calculation ..... IV.20

(c) The Model of the Reboiler

Total continuity:  $\frac{d}{dt} M_n = L_{n-1} - L_o - V$   
 ..... IV.21

where;  $L_o$  = the bottoms rate

Component continuity:  $M_n \frac{d}{dt} x_n = L_{n-1}(x_{n-1} - x_n) + V(x_n - y_n)$   
 for the M.V.C. .... IV.22

Energy equation:  $V = \frac{Q}{\lambda}$   
 ..... IV.24

where  $Q$  = the heat duty kJ/hr.

$\lambda$  = the average latent heat kJ/mol.

Vapour-liquid equilibrium:  $y_n^* = f(x_n, T_n, P)$   
 for the M.V.C. .... IV.24

Actual vapour composition:  $y_n = x_n + E_n(y_n^* - x_n)$   
 ..... IV.26



(d) The Model of the Condenser and Reflux Drum

Total Continuity:  $\frac{d}{dt} M_D = V - L_R - D$   
..... IV.27

where;  $L_R$  = the reflux rate

$D$  = the distillate rate

Component continuity:  $M_D \frac{d}{dt} x_D = V(y_1 - x_D)$   
for the M.V.C. .... IV.28

where;  $x_D$  = the reflux composition

$y_1$  = vapour composition leaving  
the topmost plate

#### IV.4.2 MODEL II : a More Comprehensive Model

The assumptions of equimolal overflow and the feed and reflux streams entering the column at their bubble points which were made in the derivation of the previous model for binary distillation columns appear to be somewhat idealised and unrealistic. Model II eliminates these two assumptions by making an energy balance across each tray. With reference to Figure III.3 the following energy balance was written in section III.3.1.

$$\frac{d}{dt} (M_n U_n) = (L_{n-1} h_{n-1} + V_{n+1} H_{n+1}) - (L_n h_n + V_n H_n) \quad \text{IV.24}$$

where  $U$  is the internal energy term and the rest of the symbols are as defined before.

The accumulation term,  $\frac{d}{dt} (M_n U_n)$ , is negligible compared with the heat fluxes through the tray and can be eliminated. This effectively means that one is assuming quasi steady-state conditions which will yield the following equation for the calculation of the vapour rate leaving each tray:

$$V_n = \frac{L_{n-1} h_{n-1} + V_{n+1} H_{n+1} - L_n h_n}{H_n} \quad \text{..... IV.30}$$

where:  $h_n = \sum h_j x_j$

$$H_n = \sum H_j y_j$$

$$h_j = \int_{T_0}^T C_{p,j} \cdot dT$$

$$H_j = h_j + \lambda_j$$

where:  $T^0$  = a reference temperature

$\lambda_j$  = the latent heat of vaporization of the  $j$ th  
component

and the rest of the symbols are as defined before.

This approach also enables us to allow for the sub-cooling of the feed and reflux streams. Thus, using this equation the binary distillation column model can be formulated more accurately as follows:

(a) The Model of a Typical Tray

$$\text{Total continuity: } \frac{d}{dt} M_n = (L_{n-1} - L_n) + (V_{n+1} - V_n) \dots\dots\dots \text{IV.31}$$

$$\begin{aligned} \text{Component continuity: } M_n \frac{d}{dt} x_n &= L_{n-1}(x_{n-1} - x_n) \\ \text{for the M.V.C.} \quad &+ V_n(x_n - y_n) + V_{n+1}(y_{n+1} - x_n) \\ &\dots\dots\dots \text{IV.32} \end{aligned}$$

$$\text{Energy equation: } V_n = \frac{L_{n-1}h_{n-1} + V_{n+1}H_{n+1} - L_n h_n}{H_n} \dots\dots\dots \text{IV.33}$$

$$\text{Fluid dynamic equation: } L_n = \frac{M_n - A}{B} \dots\dots\dots \text{IV.34}$$

$$\begin{aligned} \text{Vapour-liquid equilibrium: } y_n^* &= f(x_n, T_n, P) \\ \text{for the M.V.C.} \quad &\dots\dots\dots \text{IV.35} \end{aligned}$$

$$\begin{aligned} \text{Actual vapour composition: } y_n &= y_{n+1} + E_n(y_n^* - y_{n+1}) \\ \text{calculation} \quad &\dots\dots\dots \text{IV.37} \end{aligned}$$

(b) The Model of the Feed Tray

$$\text{Total continuity: } \frac{d}{dt} M_n = (L_{n-1} - L_n) + (V_{n+1} - V_n) + F$$

..... IV.37

$$\text{Component continuity: } M_n \frac{d}{dt} x_n = L_{n-1}(x_{n-1} - x_n) + V_n(x_n - y_n)$$

for the M.V.C.  $+ V_{n+1}(y_{n+1} - x_n) + F(x_F - x_n)$

..... IV.35

where  $F$  and  $x_F$  are the feed rate and composition respectively.

$$\text{Energy balance equation: } V_n = \frac{L_{n-1}h_{n-1} + V_{n+1}H_{n+1} - L_n h_n + Q_F}{H_n}$$

..... IV.39

$$\text{where; } Q_F = F \sum q_j x_j$$

$$\text{and } q_j = C_{P,j} (T_F - T^0)$$

$T_F$  = the feed temperature

$T^0$  = a reference temperature

$$\text{Fluid dynamic equation: } L_n = \frac{M_n - A}{B}$$

..... IV.40

$$\text{Vapour-liquid equilibrium: } y_n^* = f(x_n, T_n, P)$$

for the M.V.C. ..... IV.41

$$\text{Actual vapour composition: } y_n = y_{n+1} + E_n (y_n^* - y_{n+1})$$

calculation ..... IV.42

(c) The Model of the Reboiler

Total continuity:  $\frac{d}{dt} M_n = (L_{n-1} - L_o) - V_n$   
 ..... IV.43

Component continuity:  $M_n \frac{d}{dt} x_n = L_{n-1} (x_{n-1} - x_n)$   
 for the M.V.C.  $+ V_n (x_n - y_n)$   
 ..... IV.44

Energy equation:  $V_n = \frac{L_{n-1} h_{n-1} - L_o h_o + Q}{H_n}$   
 ..... IV.45

Fluid dynamic equation:  $L_n = \frac{M_n - A}{B}$   
 ..... IV.46

Vapour-liquid equation:  $y_n^* = f(x_n, T_n, P)$   
 for the M.V.C. .... IV.47

Actual vapour composition:  $y_n = x_n + E_n (y_n^* - x_n)$   
 calculation ..... IV.48

(d) The Model of the Condenser and Reflux Drum

Total continuity:  $\frac{d}{dt} M_D = V_1 - L_R - D$   
 ..... IV.49

Component continuity:  $M_D \frac{dx_D}{dt} = V_1 (y_1 - x_D)$   
 ..... IV.50

#### IV.4.3 TRAY EFFICIENCY

The efficiency of a tray for mass transfer depends upon three sets of design parameters:

1. The system to be separated - its composition and properties
2. Flow conditions - rates of throughput
3. Geometry - tray type and dimensions

In arriving at a value for tray efficiency, one may rely upon plant test data or on judicious use of pilot-plant efficiency measurements. If such direct information is not available, one must resort to the predictive methods.

Methods for predicting tray efficiency are of two general types:

1. Empirical or statistical methods
2. Theoretical or semi-theoretical mass transfer methods

The first method lumps the individual tray efficiencies together and thus gives the overall column efficiency (1). The second involves the prediction of individual tray efficiencies which is of more interest to dynamic simulation of tray distillation columns.

#### Theoretical Predictive Methods

The approach to equilibrium on a tray may be



defined as the ratio of the actual change in vapour composition as it passes through the tray to the change that would have occurred if the vapour had reached a state of equilibrium with the liquid. If a point on plate  $n$  is considered, this definition leads to the point efficiency:

$$E_{OV} = \frac{(Y_n - Y_{n+1})}{y_n^* - Y_{n+1}} \text{ point} \dots\dots\dots \text{IV.51}$$

where  $y_n^*$  is the vapour concentration in equilibrium with the liquid concentration at the point. This efficiency cannot exceed 1 (100 percent). If there are liquid-concentration gradients on the tray, i.e. the tray liquid is not completely mixed, then  $y^*$  will vary and  $E_{OV}$  may vary from point to point on the tray. It should be noted that an analogous efficiency expression could also be expressed on the basis of liquid concentrations. Equally well, vaporization efficiency as defined by Holland (111) could be used:

$$E_V = \frac{Y_n}{y_n^*} \dots\dots\dots \text{IV.52}$$

For the entire tray, and for vapour concentrations, the Murphree vapour efficiency is defined as follows:

$$E_{MV} = \frac{(Y_n - Y_{n+1})}{y_n^* - Y_{n+1}} \text{ plate} \dots\dots\dots \text{IV.53}$$

where  $y_n^*$  is the vapour concentration in equilibrium with the concentration of the liquid leaving the plate. Because of concentration gradients  $E_{MV}$  can exceed 100 percent.

The best established method for predicting  $E_{MV}$  is that of A.I.Ch.E. (112). It was originally developed for binary mixtures on bubble cap trays and was later extended to other types of trays (115). It is based on the sequential prediction of point efficiency, murphree plate efficiency and hence the overall column efficiency:

$$E_{OV} \longrightarrow E_{MV} \longrightarrow E_{OC}$$

On the basis of the two film model for mass transfer and relating the efficiencies to the vapour phase concentrations, the point efficiency can be expressed in terms of mass transfer units as:

$$E_{OV} = 1 - \exp(-N_{OV}) \dots\dots\dots IV.54$$

where  $N_{OV}$  is the overall mass transfer units which can be calculated from:

$$N_{OV} = \frac{1}{\frac{1}{N_V} + \frac{\lambda}{N_\ell}} \dots\dots\dots IV.55$$

where:  $N_V$  = vapour-phase transfer units

$N_\ell$  = liquid-phase transfer units

$\lambda$  = stripping factor which is given by  $\frac{mV_m}{L_m}$

$m$  = the slope of the equilibrium curve

$V_m$  = molar vapour rate, moles/hr.

$L_m$  = molar liquid rate, moles/hr.

Therefore, the evaluation of point efficiencies reduces to the prediction of the point values of  $N_V$  and  $N_\ell$ , plus the evaluation of  $m$ ,  $V_m$  and  $L_m$  for the particular

conditions under investigation.

For distillation separations, most of the resistance to mass transfer occurs in the vapour phase and therefore the calculation of  $N_V$  assumes primary importance in efficiency prediction. The A.I.Ch.E. work correlates  $N_V$  as follows:

$$N_V = \frac{0.776 + 0.116h_w - 0.290U_a\zeta_v^{0.5} + 0.0217W}{N_{scg}^{0.5}} \quad \text{..... IV.56}$$

where:

- $h_w$  = weir height in.
- $U_a$  = vapour velocity through the active area ft./sec.
- $W$  = liquid flow rate, gal./min.-ft. of the width of the flow path on the plate
- $N_{scg}$  = vapour-phase Schmidt number:  
given by  $\frac{\mu_v}{\zeta_v D_v}$

where

- $\mu_v$ ,  $\zeta_v$  and  $D_v$  are the vapour-phase viscosity, density and diffusivity respectively.

The liquid-phase transfer units may be obtained from:

$$N_l = k_l a \theta_l \quad \text{..... IV.57}$$

where

- $k_l$  = liquid-phase transfer coefficient ft./sec.
- $a$  = effective interfacial area for mass transfer, sq.ft./cu.ft. of the froth on the tray
- $\theta_l$  = residence time of liquid in the froth zone sec.

The froth zone represents a volume with base equal to the active area of the tray and height  $h_f$  equal to the froth level that would be observed through a window for viewing contacting action on the tray. In the absence of visual observations,  $h_f$  can be calculated from the A.I.Ch.E. equation:

$$h_f = 2.53U_a^2\zeta_v + 1.89h_w - 1.6 \dots\dots\dots \text{IV.58}$$

where:

- $h_f$  = froth height in.
- $U_a$  = linear vapour velocity through  
the active area ft./sec.
- $\zeta_v$  = vapour density lb/cu.ft.
- $h_w$  = weir height in.

Thus the liquid residence time is

$$\theta_\ell = \frac{h_f A_a \phi_t}{12q} \dots\dots\dots \text{IV.59}$$

and since the average relative froth density on the tray,  $\phi_t$ , is equal to  $\frac{h_\ell}{h_f}$ ,

$$\theta_\ell = \frac{h_\ell A_a}{12q} \dots\dots\dots \text{IV.60}$$

where:

- $q$  = liquid flow rate cu.ft./sec.
- $A_a$  = active area sq.ft.
- $h_\ell$  = pressure drop through the  
aerated liquid in.
- $\phantom{h_\ell} = \beta h_{ds}$
- $h_{ds}$  = calculated height of clear  
liquid over the disperser in.
- $\beta$  = aeration factor calculated from  
a correlation given by Perry(1)

For sieve plates:

$$h_{ds} = h_w + h_{ow} + \frac{h_{hg}}{2} \dots\dots\dots \text{IV.61}$$

where:

- $h_w$  = weir height in.
- $h_{ow}$  = height of the liquid  
over the weir (inches of clear liquid)
- $h_{hg}$  = hydraulic gradient  
across the plate (inches of clear liquid)

where the height of the liquid over the wier may be calculated from the Francis weir equation (1).

The mass-transfer coefficient of equation IV.57 is carried as a product with the interfacial area to give a volumetric mass-tranfser coefficient:

$$K_{\ell} a = (1.065 \times 10^4 D_{\ell})^{0.5} (0.26 U_a \zeta_v^{0.5} + .15) \dots\dots \text{IV.62}$$

where  $D_{\ell}$  is the liquid diffusion coefficient in sq.ft./hr. The rest of the symbols are as defined before.

As noted before, because of incomplete mixing, it is necessary in most instances to convert the point efficiency  $E_{OV}$  to Murphree plate efficiency  $E_{MV}$ , since only in small laboratory columns and under special conditions is the assumption  $E_{OV} = E_{MV}$  likely to be valid. The A.I.Ch.E. method suggests an eddy diffusion model to convert point efficiency to Murphree plate efficiency. According to this model,

$$\frac{E_{MV}}{E_{OV}} = \frac{1 - \exp(-n' - N_{pe})}{(n' + N_{pe}) \left\{ 1 + \frac{n' + N_{pe}}{n'} \right\}} + \frac{\exp(n') - 1}{n' \left\{ 1 + \frac{n}{n' + N_{pe}} \right\}} \dots\dots\dots \text{IV.63}$$

where

$$n' = \frac{N_{pe}}{2} \left( \sqrt{1 + 4\lambda \frac{E_{OV}}{N_{pe}}} - 1 \right)$$

$$N_{pe} = \text{peclet number} = \frac{z_{\ell}^2}{D_E \theta_{\ell}}$$

$z_{\ell}$  = length of the liquid travel ft.

$\lambda$  = stripping factor

$D_E$  = eddy diffusion coefficient sq.ft./hr.

The value of  $\theta_{\ell}$  can be calculated from equation IV.60.

The term  $D_E$  is an eddy diffusion coefficient. For bubble-cap trays it may be obtained from

$$D_E^{0.5} = 0.0124 + 0.0171U_a + 0.0025 \frac{q'}{w} + 0.015h_w$$

..... IV.64

where

$q'$  = liquid flow rate gal/min.

$w$  = width of the flow path ft.

$$= \frac{d_c + d_i}{2}$$

$d_c$  and  $d_i$  = column and liquid inlet diameter

For sieve trays it is suggested that the values of  $D_E$  obtained from equation IV.64 should be multiplied by 1.25 (1).

The effect of entrainment has not been considered since most columns normally operate in the region of minimum entrainment.

From a computational viewpoint, if individual efficiencies are evaluated independently, the A.I.Ch.E. method may lead to further problems in the calculation of vapour phase compositions. For example, the sum of the calculated vapour phase mole fractions may not



add to unity. This problem can be overcome by calculating the mole fraction of one of the components by difference as:

$$y_i = 1 - \sum_{k=1}^j y_k \dots \dots \dots \text{IV.65}$$

According to the physical properties of the components of a system, the point efficiency may be related to only one of the vapour or the liquid transfer units. In equation IV.55, one of the values of  $\frac{1}{N_v}$  or  $\frac{\lambda}{N_l}$  may be much larger than the other. If  $\frac{1}{N_v}$  is much larger than  $\frac{\lambda}{N_l}$ , the value of  $\frac{\lambda}{N_l}$  becomes negligible and may be ignored. Such a system is controlled by the vapour phase resistance. If the opposite is true then  $\frac{1}{N_v}$  can be ignored. Such a system is defined as liquid film controlling. The determination of the controlling film element is affected by the value of the stripping factor,  $\lambda$ , which is a direct function of the slope of the equilibrium curve. For a system with a flat equilibrium curve,  $\lambda$  may be very small and thus  $\frac{\lambda}{N_l}$  may be ignored giving a vapour film controlled system. On the other hand, the liquid systems with a steep equilibrium curve usually yield a liquid film controlling system.

#### IV.4.4 EFFICIENCY OF THE REBOILER

The form of the equation known as the vaporization efficiency is obtained by application of the Murphree efficiency to the reboiler stage. The value of  $y_{n+1}$  will be zero in equation IV.53 since no vapour is entering the stage. Unless some experimental values of vaporization efficiency are available, the application of this efficiency definition will result in the further problem of evaluating the vaporization efficiency. It was therefore decided to use the following efficiency definition for the reboiler as suggested by Dilfanian (115):

$$E_{OV} = \left( \frac{y_n - x_n}{y_n^* - x_n} \right)_{\text{reboiler}} \dots\dots\dots \text{IV.66}$$

#### IV.4.5 PHASE EQUILIBRIA

##### Thermodynamics of Vapour-liquid Equilibrium

Thermodynamic equilibrium is defined as the final point of a reversible process and from this definition the condition of equilibrium can be expressed mathematically. Thus if a system were at its equilibrium state, there would be no change in its pressure, temperature and conditions. Moreover, the change in free energy, work, heat and entropy of the system under equilibrium would be zero.

Making the usual assumptions, it can be shown (113,122), that the fundamental equation of phase equilibrium can be written as:

$$f_i^L = f_i^V \dots\dots\dots \text{IV.67}$$

where  $f$  refers to the fugacity and  $L$  and  $V$  refer to the liquid and vapour phases respectively.

Equation IV.67 is of little practical use unless the fugacities can be related to experimentally accessible quantities  $x$ ,  $y$ ,  $T$  and  $P$  where  $x$  and  $y$  stand for the mole fractions of liquid and vapour phases respectively.  $P$  is the total pressure of the system which is assumed to be the same for both phases and  $T$  is the absolute temperature. The desired relationship between fugacities and experimentally accessible quantities is facilitated by two auxiliary functions which are given the symbols  $\psi$  and  $\gamma$ . The first of these, the fugacity coefficient  $\psi$  relates the vapour-phase fugacity  $f_i^V$  to the mole fraction  $y_i$ , and the total pressure  $P$ . It is defined by

$$\psi_i = \frac{f_i^V}{y_i P} \dots\dots\dots \text{IV.68}$$

The activity coefficient  $\gamma$  relates the liquid-phase fugacity  $f_i^L$  to the mole fraction  $x_i$  and to a standard state fugacity  $f_i^{OL}$ . It is defined by

$$\gamma_i = \frac{f_i^L}{x_i f_i^{OL}} \dots\dots\dots \text{IV.64}$$

From equations IV.67, IV.68 and IV.69 the equilibrium equation for any component  $i$  becomes

$$\psi_i y_i P = \gamma_i x_i f_i^{OL} \dots\dots\dots \text{IV.70}$$

For multicomponent systems, rigorous methods for the prediction of  $\psi_i$ ,  $\gamma_i$  and  $f_i^{OL}$  are available as suggested by Prausnitz (113) while Dilfanian (115) provides an example of the application of these methods. However, for binary non-azeotropic systems at moderate pressures of up to 5 atm., if the vapour can reasonably be assumed to be a perfect gas,  $\psi_i$  can be taken as unity and, ignoring the Poynting correction, the vapour liquid equilibrium may be approximated by:

$$y_i P = \gamma_i x_i P_i^O(T) \dots\dots\dots \text{IV.71}$$

where  $P_i^O$  is the saturation vapour pressure of component i at the system temperature T.

The activity coefficients  $\gamma_i$  can be predicted using experimental data and either Van Laar, Wilson or NRTL equations. The choice largely depends on which equation best represents the vapour-liquid equilibrium of the system under consideration. The Van Laar equations have been used for the activity coefficient prediction in this research and these are

$$\log \gamma_1 = (2B-A)x_2^2 + 2(A-B)x_2^3 \dots\dots\dots \text{IV.72}$$

$$\log \gamma_2 = (2A-B)x_1^2 + 2(B-A)x_1^3 \dots\dots\dots \text{IV.73}$$

where

$$A = \frac{(x_1-x_2) \log \gamma_2}{x_1^2} + \frac{2 \log \gamma_1}{x_2} \dots\dots\dots \text{IV.74}$$

$$B = \frac{(x_2-x_1) \log \gamma_1}{x_2^2} + \frac{2 \log \gamma_2}{x_1} \dots\dots\dots \text{IV.75}$$

The constants A and B are normally averaged over at least four values calculated from experimental data at various temperatures to account for the variation of activity coefficient with temperature.

Saturation vapour pressure data are most conveniently related to temperature by the Antoine equation

$$\log P_i^O(T) = C_1 - \frac{C_2}{C_3 + T} \dots\dots\dots \text{IV.76}$$

where the constants  $C_1$ ,  $C_2$  and  $C_3$  can be evaluated from three sets of vapour-pressure-temperature data.

#### IV.4.6 PHYSICAL PROPERTY PREDICTION

Tray efficiency prediction by the A.I.Ch.E. method requires the knowledge of an almost complete spectrum of the physical properties of the liquid system ranging from the critical properties to the vapour and liquid diffusivities of the components. Usually, such data are not available and need to be estimated. The equations and the methods proposed for the estimation of the physical properties are given in Appendix B.

#### IV.5 SIMULATION OF BINARY DISTILLATION COLUMNS

The central theme in dynamic simulation is usually the solution of the differential equations that essentially constitute the mathematical model of the system being simulated. The philosophical approach to the solution of a single or a set of differential equations is an analogue of the principle of "causality" which states that the future can be predicted from a knowledge of the present. The connotation of this in mathematical sense is that if a variable,  $x$  obeys the deterministic differential equation

$$\frac{dx}{dt} = f(x,t)$$

the state (value) of  $x$  at time  $t+\delta t$  depends only on the state of  $x$  at time  $t$  and not how  $x$  reached the state at time  $t$ . This principle is equally applicable to the solution of stochastic differential equations except that in this case it will be more relevant to talk about the probability law of  $x$  as opposed to its state. Therefore, if the state of a variable  $x$  at time  $t$  is known together with its differential equation, its state at time  $t+\delta t$  can also be predicted.

If the dynamic simulator is being used to predict, say, a steady state starting from a given set of conditions, the closer the starting point to the steady state the less the effort needed to reach the steady state. As regards computer simulations, this effort is, simply, the computation time. Thus, a judicious choice



of the starting conditions can give us a head start in saving computer time. As far as binary distillation columns are concerned, life is somewhat easier in that a realistic set of starting conditions can easily be obtained by a steady-state shortcut method such as the McCabe-Thiele. This approximate steady-state can then be refined by the dynamic simulator more efficiently. The two versions of binary distillation column simulation compiled in this research adopt this technique to overcome the initialisation problem. The first simulator is based on Model I while the second one uses Model II. Both simulators offer a choice for tray efficiency calculation in case the experimental values of tray efficiencies are available.

The simulators can, therefore, be conveniently divided into two different parts namely,

- (i) the initialisation by approximate steady-state calculations to obtain the temperature and composition profiles and the flow rates
- (ii) the dynamic part to perform the dynamic simulation

#### IV.5.1 INITIALISATION

1. Specify a realistic separation;  $x_D$  and  $x_B$ .
2. Guess a reasonable value for the reflux ratio and fix  $x_D$
3. Adjust the reflux ratio to achieve the specified separation by iterating around the reflux ratio until the calculated value of  $x_B$  is within a

tolerance of the specified value. This can be done by a Wegstein type algorithm to achieve speedy convergence (subroutine SDWEG). However, care must be taken to ensure that the computed reflux ratio is physically meaningful.

4. Perform a McCabe-Thiele steady-state calculation to obtain approximate temperature and composition profiles and vapour and liquid rates. If efficiency calculations are requested, compute approximate tray efficiencies based on these approximate profiles and flowrates (subroutine SSMODL).

The subprograms that perform these functions are named, SDWEG, SDSSWEG, and SSMODL respectively.

It must be noted that this exercise is purely for the initialization of the dynamic modules and its accuracy is of secondary importance. Thus if a reasonable set of temperature and composition profiles are available together with the corresponding vapour and liquid rates, then this exercise becomes redundant.

## IV.5.2 ALGORITHMS

### IV.5.2.1 THE MAIN PROGRAM

The algorithm for the main program segment is as follows:

1. Read in the physical data including:
  - (i) the separation for the steady-state calculations, total number of plates, number of components and the feed plate
  - (ii) the Brambilla equation constants
  - (iii) vapour-pressure-temperature data for the calculation of Antoine equation constants
  - (iv) temperature-composition data for the calculation of Van Laar equation constants
  - (v) the latent heats of vaporisation of the components
  - (vi) the specific heat capacity constants if model II is being used
  - (vii) if efficiency calculations are requested, then read in the physical properties of the components of the liquid system and the geometrical design information including tray type and dimensions
  - (viii) read in the integrator parameters and the print frequency
  - (ix) read in the frequency with which the efficiency calculations are to be repeated and the end of the simulation time
2. Compute reflux ratio for the specified separation

(subroutine SDWEG)

3. Compute approximate vapour and liquid rates and temperature and composition profiles and also efficiencies if requested (subroutine SSMODL).
4. Initialise the integrated variables in the dynamic simulator and adjust any number of the variables as necessary.
5. Set  $TIME=0$ , and zero all of the integrator pass numbers.
6. CALL the dynamic module.
7. If  $TIME$  is equal to  $ENDTIME$ , then stop.
8. Set  $TIME=TIME+DT$ ; where  $DT$  is the integration step size.
9. Return to step 6 and continue.

#### IV.5.2-2 ALGORITHM FOR THE SOLUTION OF THE DYNAMIC MODEL I

In addition to the integrator parameters, certain flags are chosen to enable easy communication with the simulator in order to display the dynamic characteristics of selected trays during a run or to control the frequency of the efficiency calculations. These flags must be set before the dynamic simulator is entered.

#### The Algorithm

1. Store efficiency values if available and print information in accordance with the specified print interval.

2. Compute tray liquid hold-up and composition derivatives.
3. Integrate differential equations by calling the integrator : the SDINT subroutines.
4. Perform bubble point calculations in order to compute the equilibrium temperatures.
5. Compute the liquid rates leaving each tray from the truncated Brambilla equation.
6. Calculate the boil-up rate.
7. Compute efficiencies if requested and in accordance with the specified frequency.
8. Calculate the actual composition of the vapour leaving each tray.
9. Test for the step completion if the higher order integration methods are being used. If the step is not completed, return to step 2 and continue until the pass numbers of the higher integration methods are zeroed as signalled by the integrator.
10. Return.

#### IV.5.2-3 ALGORITHM FOR THE SOLUTION OF DYNAMIC MODEL II

This algorithm is much the same as the algorithm for the solution of model I except that the step 6 is excluded and the following calculations are performed instead:

- (i) compute enthalpies of the liquid and vapour streams leaving each stage
- (ii) calculate the enthalpies of the feed and reflux

streams

- (iii) compute the individual vapour rates leaving each stage starting from the reboiler

The complete listings of the programs are given in Appendix B.1.1 (Microfishe)



#### IV.6 STIFFNESS ASPECTS OF DISTILLATION COLUMN SIMULATION

In a system simulation stiffness essentially materializes when the system's differential equations have very small time constants compared with the dominant time constants of the system. Thus if the integration step size used to solve them is not sufficiently small, the simulation can become very inaccurate, if not unstable or divergent.

Stiffness problem in distillation simulation are even more chronic in that none of the compositions can exceed unity. Once a composition exceeds unity due to the inaccuracies induced by a large integration step size, then the bubble point calculations will almost certainly diverge. In such cases, there exists a critical step size that would accommodate any stiffness situation and beyond which the integration step size must not be increased. Various attempts have been made to relate the critical step size to the largest eigenvalue of a linear system (117). This approach is by no means a panacea inasmuch as it only covers linear systems and, moreover, it is dependent upon the integration method.

In a complex non-linear system such as distillation, the critical step size must eventually be determined by trial-and-error and a few computer runs. Naturally, a small critical step size means very long running times and this may not be desirable. Thus attempts must be made to compensate for the consequen-

tial loss of computational efficiency by other means. Under these conditions, the following techniques were implemented and found to be effective:

- (i) the number of interstep bubble point iterations were reduced considerably by using the temperature of the previous integration step as the guess temperature for the present step
- (ii) the tray efficiency need not be calculated at every step but at a predetermined frequency as they are almost time-invariant during a run
- (iii) the use of a variable step integrator

C H A P T E R F I V E  
OPEN-LOOP SIMULATION RESULTS  
and  
EXPERIMENTAL VERIFICATIONS

## V.1 OPEN-LOOP SIMULATION STUDIES

The simulators discussed in the previous chapter were used to simulate the 3-inch, 10 sieve-tray distillation column that was discussed in Chapter III. In order to enable comparison between the predictions of the two simulators, it was assumed that the feed and reflux streams entered the column as saturated liquids at their bubble points. The critical step size for this column was found to be  $0.4 \times 10^{-4}$  hour and since these were purely theoretical studies intended to achieve an understanding of the dynamic character of the column, it was decided to adhere to the simple Euler integration method to avoid excessive running times. It was also assumed that the column was under open-loop conditions and aside from the flow and heat input regulations, the only control actions were due to the reflux drum and reboiler level controllers. These conditions are sometimes referred to as the "natural control" conditions. The schematic diagram of the column under natural control conditions is depicted in Figure V.1. The binary liquid system was trichloroethylene and tetrachloroethylene with the trichloroethylene being the most volatile component with a feed mole fraction of 0.4. The geometric configuration of the column is discussed in Chapter III while the properties of the liquid system are given in Appendix C.

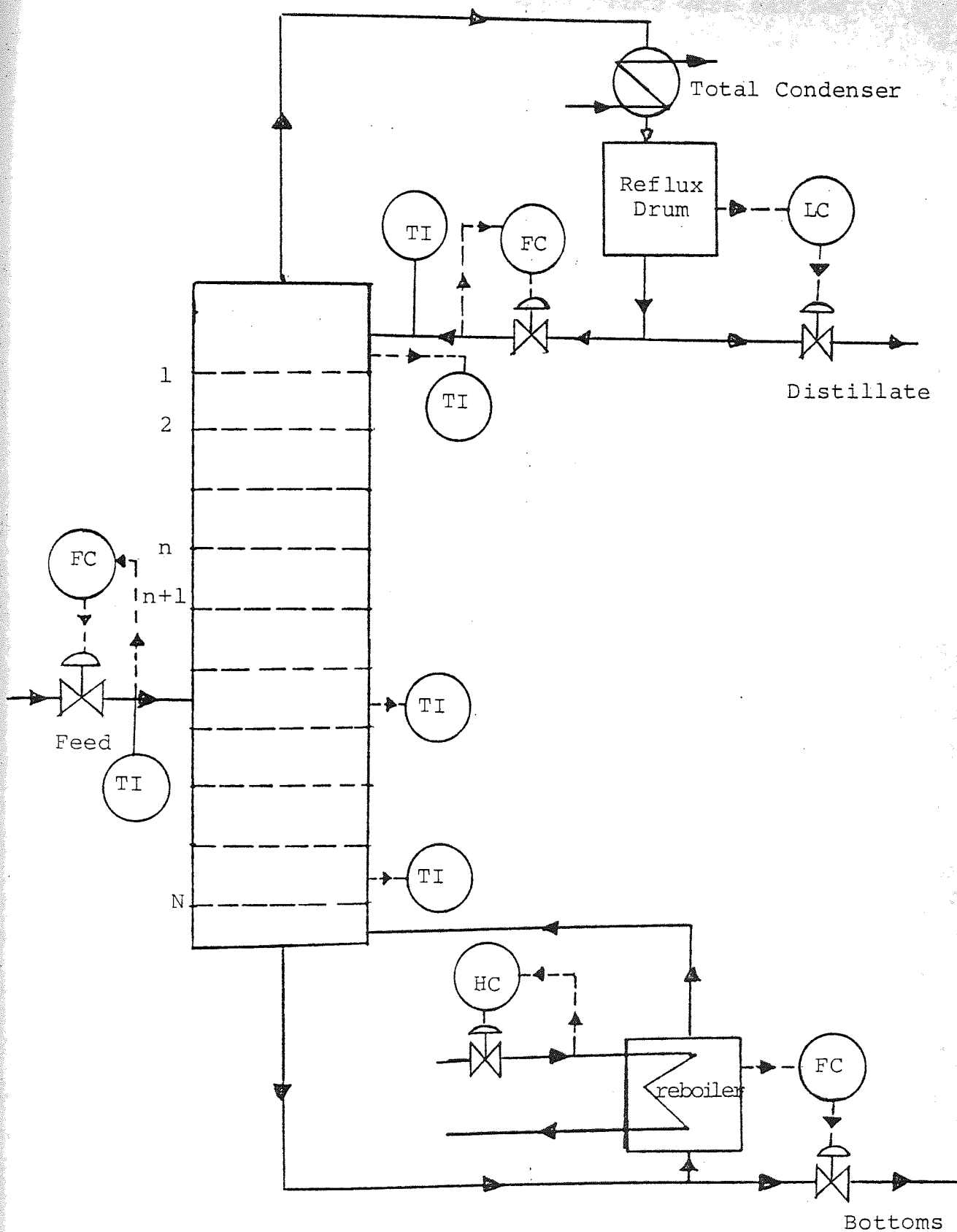


FIGURE V.1 The Schematic Diagram of the Column under "Natural Control"

The following computer experiments were carried out:

- (i) the prediction of a more accurate steady state starting from the approximate McCabe-Thiele predictions: Figures V.2 and V.3
- (ii) the response to a step change in the feed rate introduced at steady state: Figures V.4 and V.5
- (iii) the response to a step change in the feed composition introduced at steady state: Figures V.6 and V.7

Since the effects of subcooling of the feed and reflux streams on the column's performance were unknown, it was decided to use the simulator based on model II, discussed in Chapter IV, to study these effects. This was another example of how dynamic simulation could be effectively used to obtain a deeper insight into the behaviour of different processes. In this context, one more simulation experiment was carried out to study the response of the column to the step changes in the feed and reflux temperatures. The results are shown in Figures V.8 and V.9.

During these experiments the feed rate was chosen as 10 mole/hr. and the reboiler holdup was 60 moles. These simulation studies were necessary to

- (i) ensure that the simulators were functioning properly
- (ii) achieve an understanding of the dynamic character of the column



Figure V.2  
Simulation Experiment No.1  
Steady-State Prediction by the Two Models starting from  
the McCabe-Thiele Approximation

PLATE NUMBER= 1.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 96.800  
REFLUX RATIO= 2.000

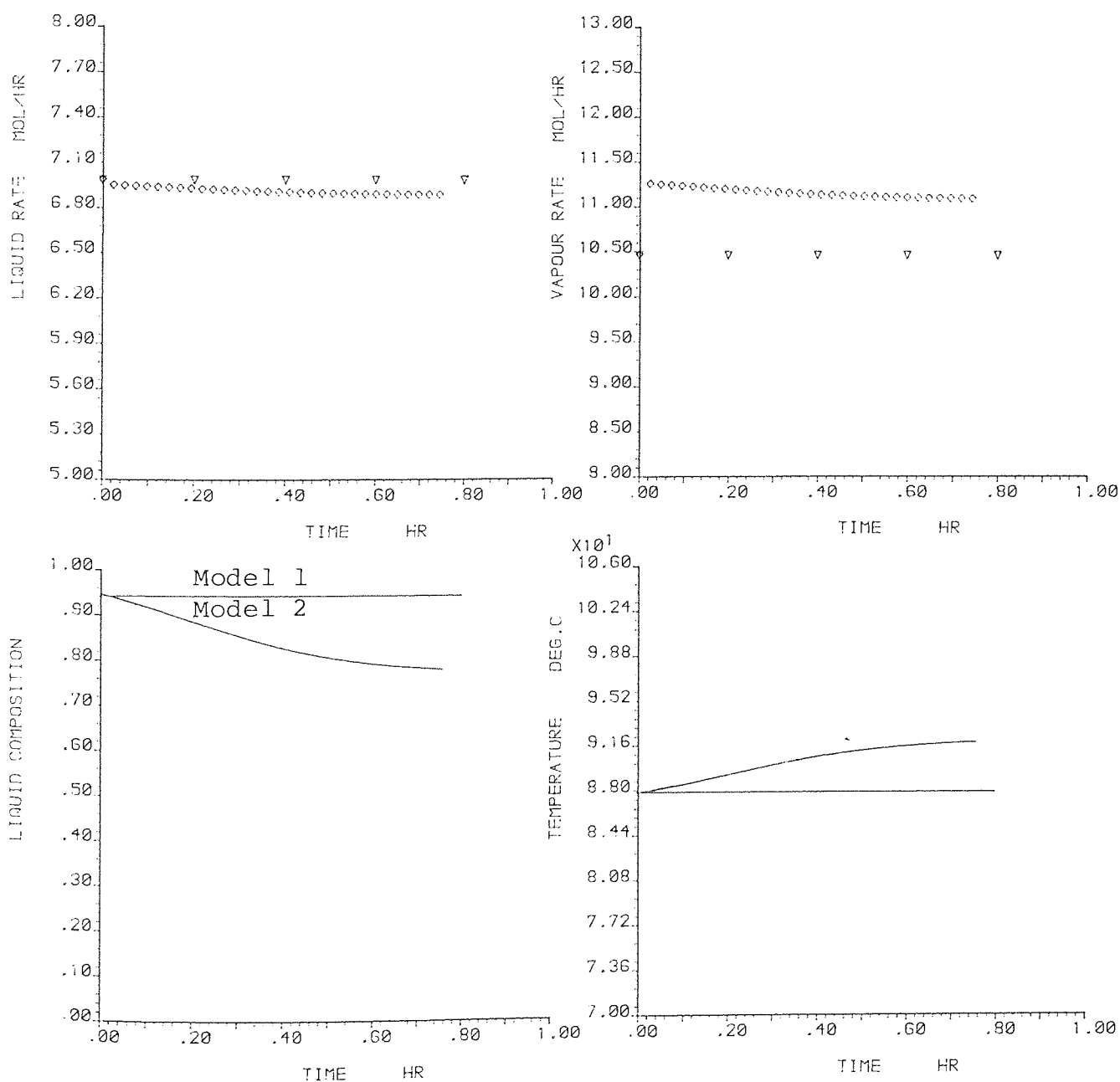


Figure V.3  
Simulation Experiment No.1 continued

PLATE NUMBER= 10.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 65.00  
REFLUX TEMPERATURE= 66.900  
REFLUX RATIO= 2.000

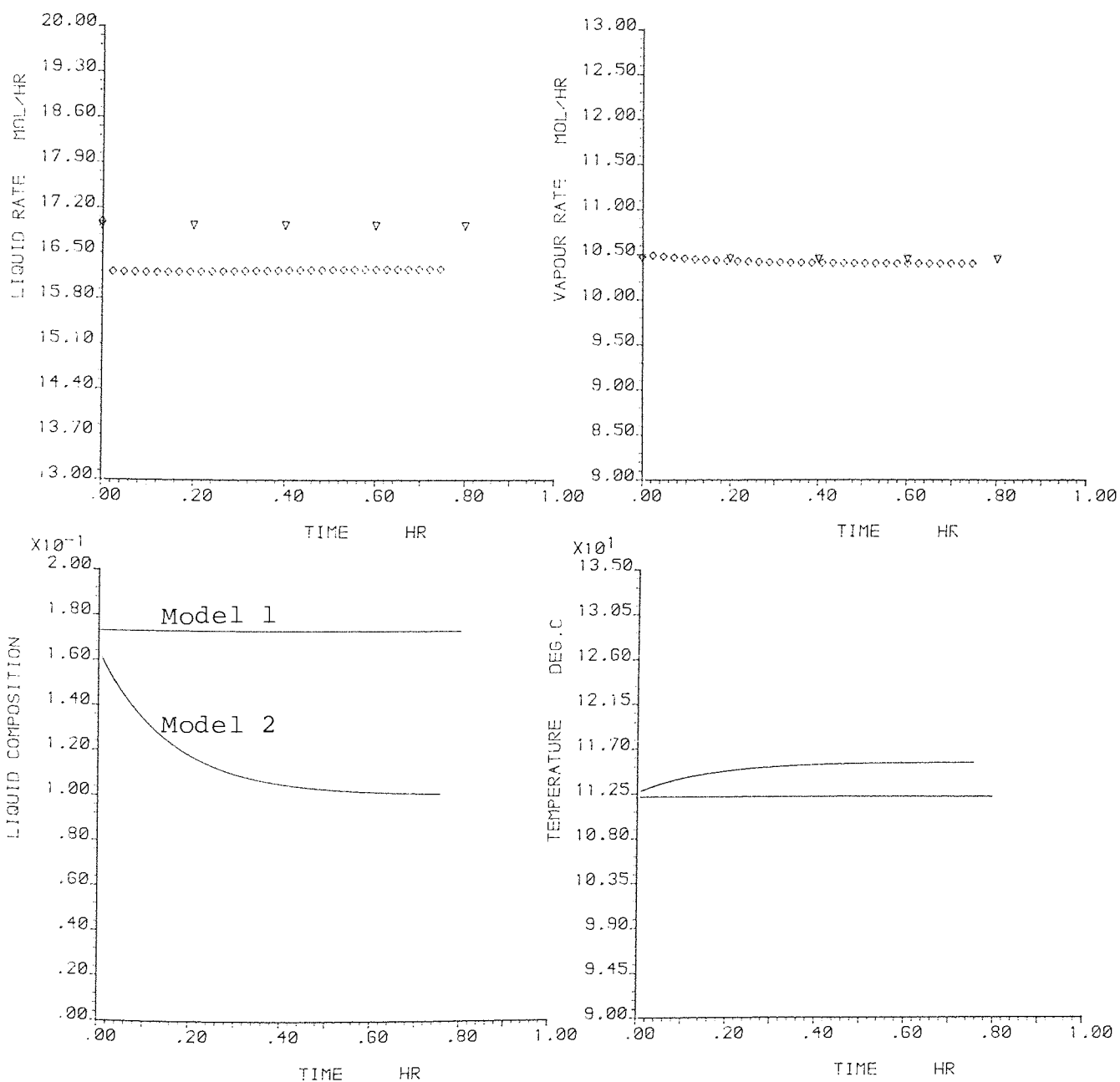


Figure V.4  
Simulation Experiment No.2  
The Open-Loop Response of the Column 10% Step Increase  
in the Feed Rate

PLATE NUMBER= 1.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 86.900  
REFLUX RATIO=2.000

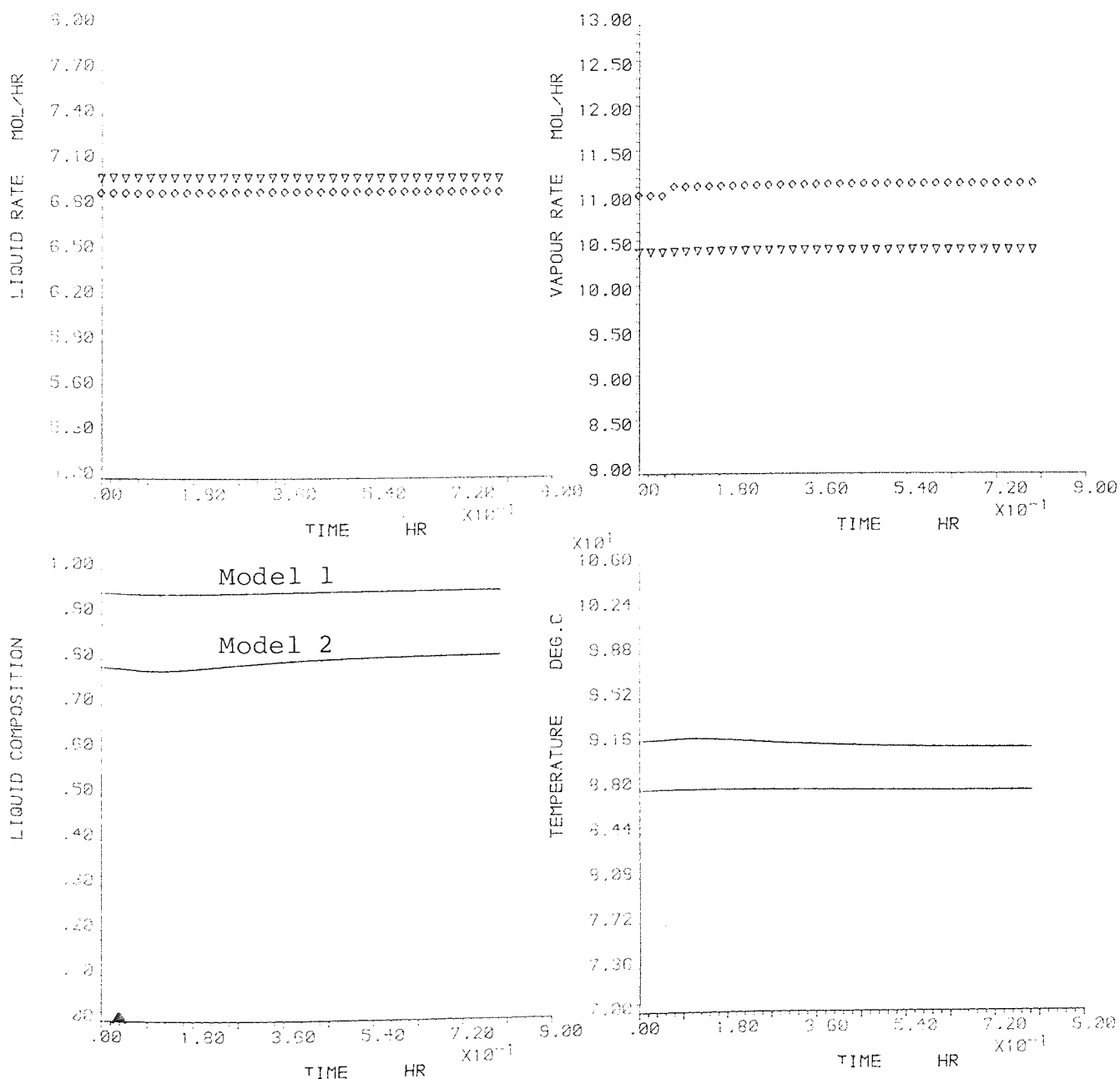


Figure V.5  
Simulation Experiment No.2 continued

PLATE NUMBER= 10.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 86.900  
REFLUX RATIO= 2.000

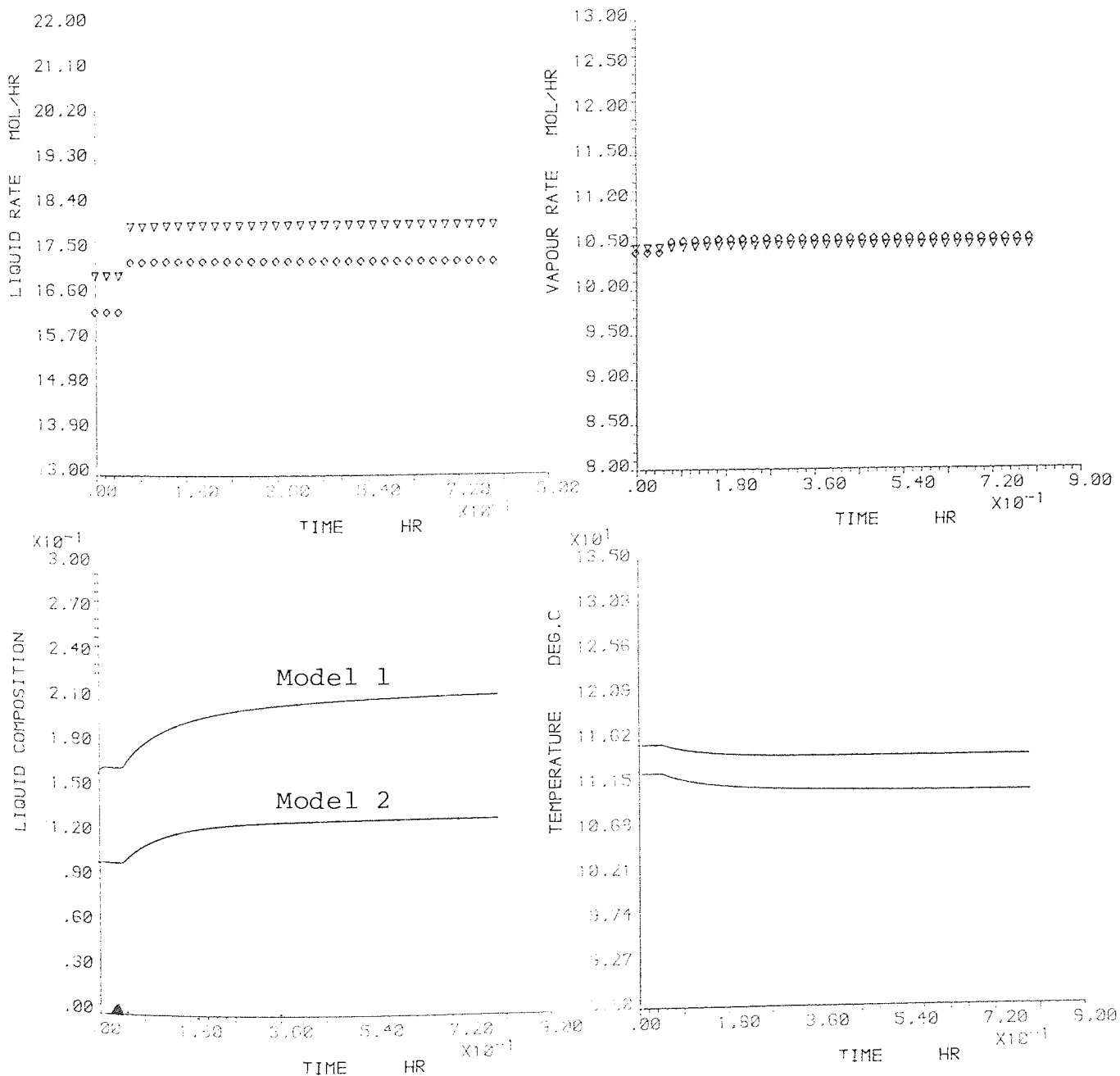


Figure V.6  
Simulation Experiment No.3  
The Open-Loop Response of the Column to 10% Step Increase  
in the Feed Composition

PLATE NUMBER= 1.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 86.900  
REFLUX RATIO= 2.1

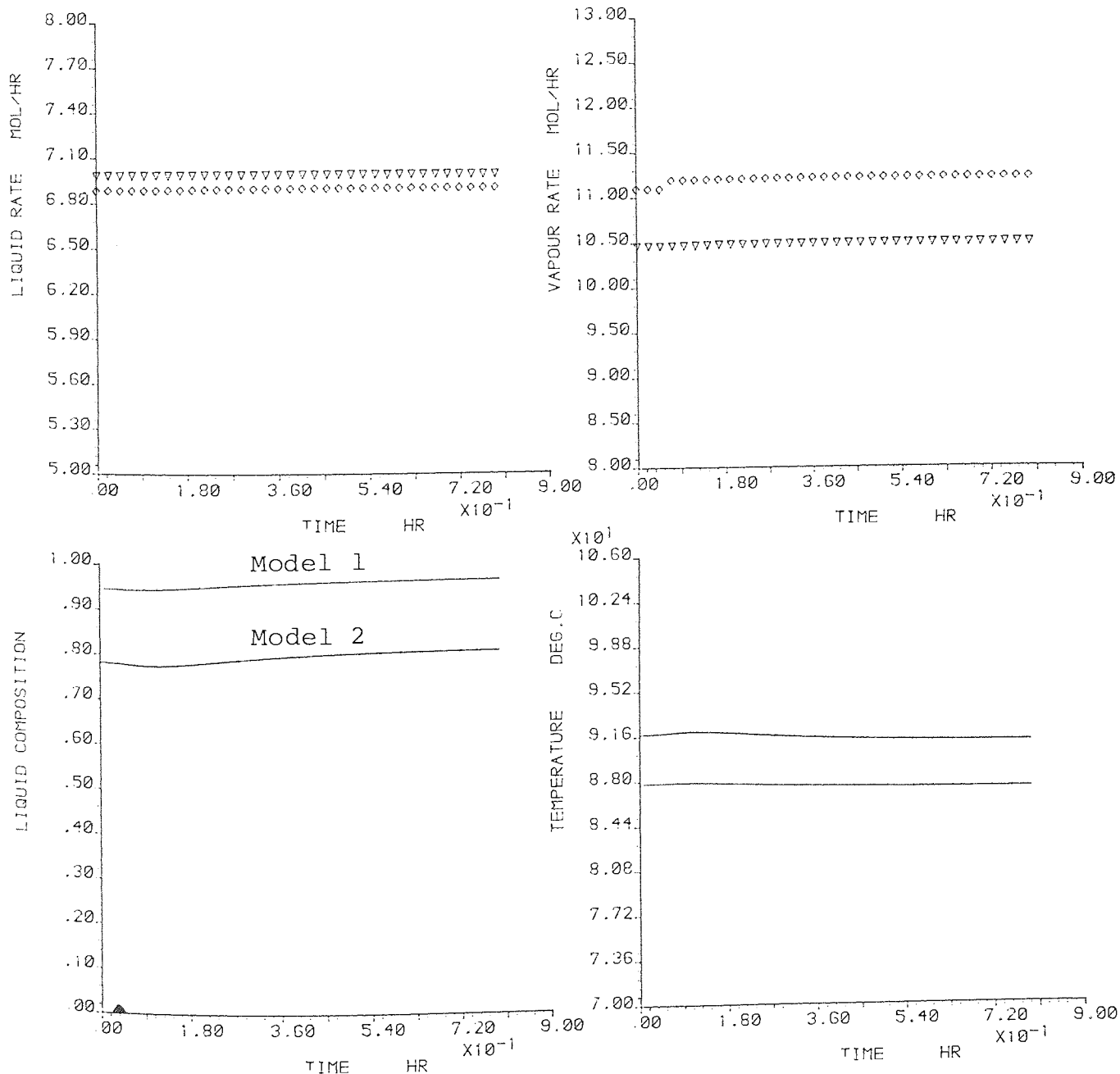


Figure V.7  
Simulation Experiment No.3 continued

PLATE NUMBER= 10.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 86.900  
REFLUX RATIO= 2.000

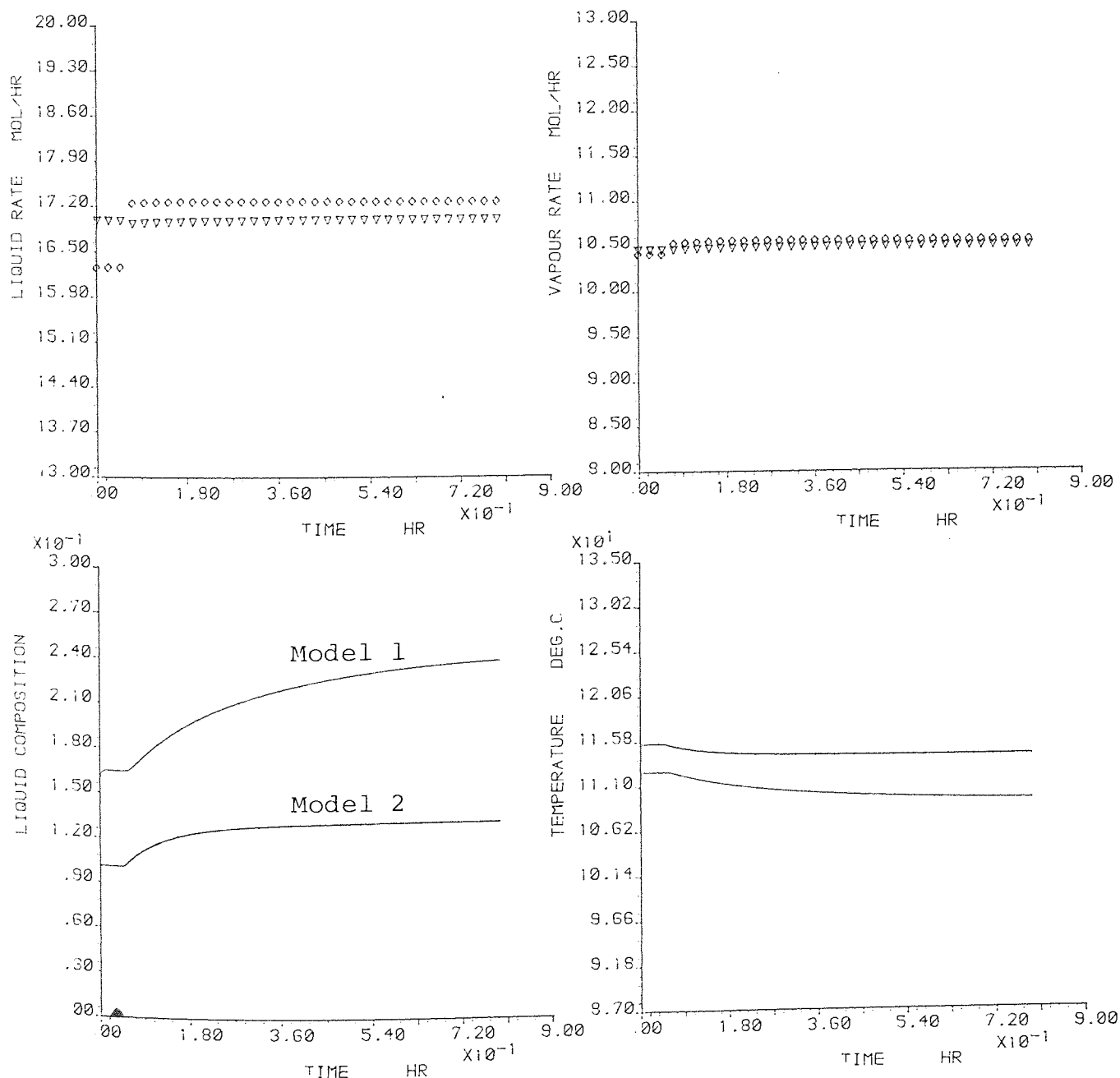




Figure V.8

Simulation Experiment No.4

The Open-Loop Response of the Column to Consecutive Step Decreases in the Feed and Reflux Stream Temperatures down to the Room Temperature Predicted by the Simulator No.2

PLATE NUMBER= 1.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 86.900  
REFLUX RATIO= 2.000

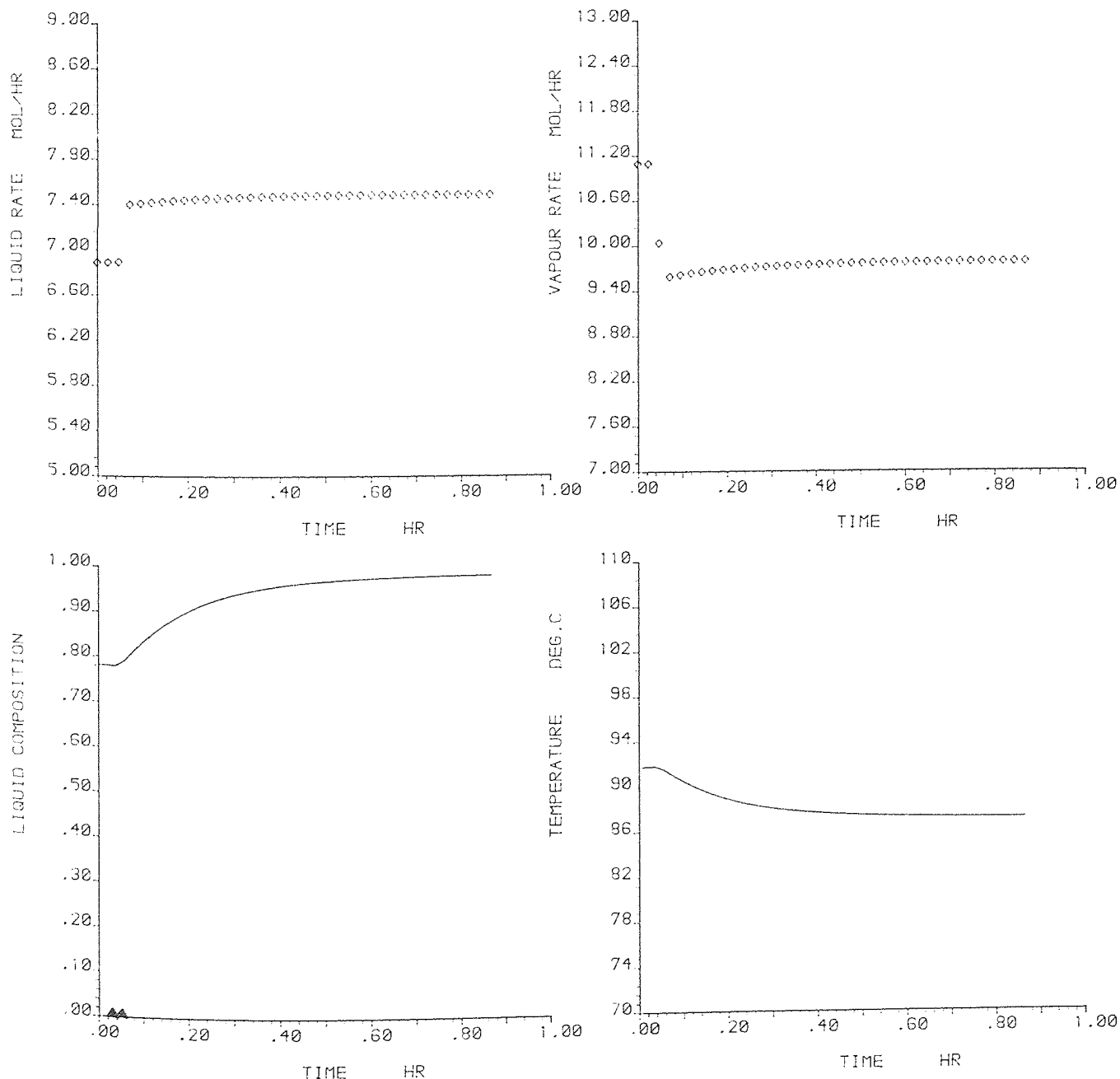
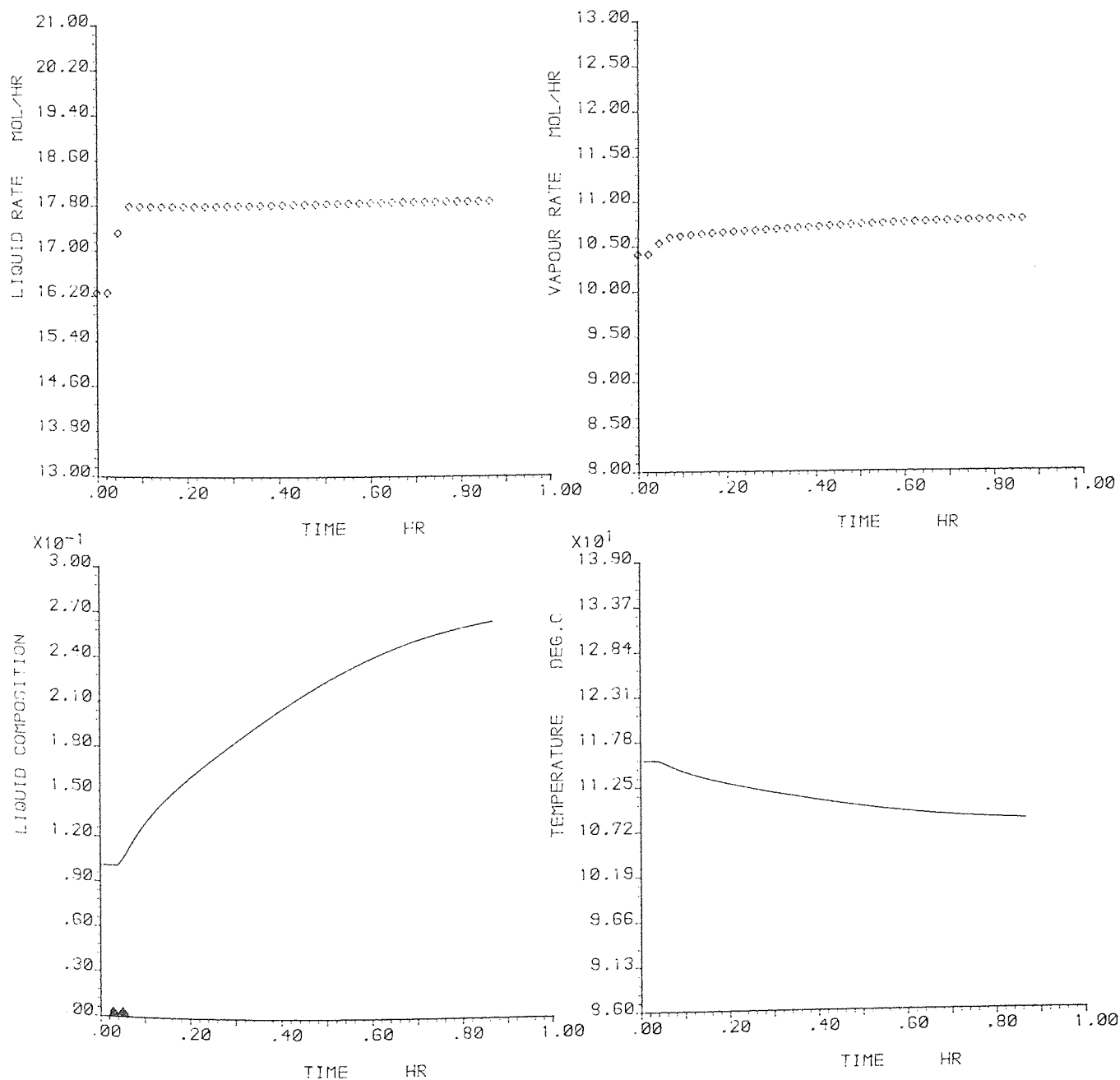


Figure V.9  
Simulation Experiment No.4 continued

PLATE NUMBER= 10.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 85.00  
REFLUX TEMPERATURE= 86.800  
REFLUX RATIO= 0.000



(iii) modify the instrumentation necessary for the dynamic studies and control of the actual column. E.g. as a result of the simulation experiment No.4, it was decided to measure the feed and reflux stream temperatures

(iv) compare the performances of the two models for binary distillation discussed in Chapter IV.

We shall return to this point during the design of the Kalman filters

The simulations were run on the University's 1904S computer. Exact statistics for the running times are difficult to provide as it is virtually impossible to estimate the overheads. Also, the frequency with which the efficiency calculations are repeated has a strong bearing on the running times. Nonetheless, despite these variables it can be assumed that the ratio of the simulation time to real computer time is approximately 4 to 1 when the efficiencies are recomputed every 3 minutes and the results are also printed out every 3 minutes.

## V.2 THE OPEN-LOOP EXPERIMENTS

In order to ensure that simulator II, discussed in Chapter IV, is a reasonable representation of the static and dynamic characters of the column, it was decided to check its predictions of the topmost and lowermost tray temperatures experimentally. Thus, the following open-loop experiments were carried out during which the column operated under "natural" control only (see Figure V.1). These were:

- (i) steady-state operation
- (ii) the response to a step change in the feed rate

The process equipment is depicted in Figure III.1, in Chapter III. The two proportional level-controllers used to control the reflux drum and the reboiler levels were tuned on-line such that steady levels were maintained by the manipulations of the top and bottom product valves: as shown in Figure V.1. The feed, reflux and heat input rates were maintained by refreshing the settings of their associated analogue output channels.

The liquid system components were trichloroethylene and tetrachloroethylene whose properties are tabulated in Appendix C.

A software package known as the HADIOS Executive is available which enables the user to communicate with the column, through HADIOS, from a BASIC program. This package is intended to enable the user to access

the column regularly at a chosen time frequency. The version of this software used by Webb (27) has been modified in this research. These modifications are hoped to render the package more flexible in the following ways:

- (i) they provide a simpler communication scheme with the package
- (ii) they enable the user to service more than one digital output channel at a time
- (iii) they enable the electrical noise to be smoothed out to some extent during the scanning of the analogue input channels

The listings of the latest version of the HADIOS Executive and its modifications for this research are given in Appendix D.

### V.2.1 THE STEADY-STATE EXPERIMENTS

A number of steady-state experiments were carried out on the distillation column under the same operational conditions. The steady-state temperature measurements were checked against the predictions of the simulator II. The procedure followed is:

1. Carry out the experiment ensuring that the column runs at steady-state for at least 20 minutes and record the following information for about 20-30 minutes.
  - (i) the top and bottom tray temperatures
  - (ii) the feed rate, composition and temperature
  - (iii) the reflux rate and temperature
  - (iv) the heat input rate
  - (v) the reboiler and reflux drum levels
2. Feed all the information obtained in step 1 (except the tray temperatures) into the simulator and drive the simulator to steady state.
3. Plot the tray responses on the 1904S computer with the experimental tray temperatures, from step 1, superimposed on their predicted counterparts.

Since the simulator assumes adiabatic operational conditions, the actual heat input rate recorded during the experimental runs must be corrected for the inherent heat losses that take place during the operation of the column. In other words



$$Q_{\text{adiabatic}} = Q_{\text{actual}} - \delta Q_{\text{lost}}$$

A typical set of the experimental input data used to test the simulator is given in Table V.1. since the standard print-out of the simulator is based on a feed rate of 10 moles/hr, all the rates and holdups need to be scaled. The simulator expects the scale factor to handle the calculations such that the actual experimental conditions are simulated.

The details of the calculation procedure for the estimation of the heat losses are given in Appendix C. The graphic results are shown in Figures V.10 and V.11. The accuracy of the steady-state temperature predictions were found to be within  $\pm 0.6^{\circ}\text{C}$ . for the topmost and lowermost trays.

### V.2.2 THE RESPONSE TO A STEP INCREASE IN THE FEED RATE

Amongst the possible load changes that can be introduced, throughput changes are normally more testing as far as the response and operation of the column is concerned. It was therefore decided to adhere to this type of disturbance because if the prediction of the column's response to throughput changes is reasonably accurate, it could be assumed that the prediction of its response to composition changes could also be made with a comparable accuracy. Moreover, to ensure that the simulator is a reasonable representation of the column under extremely transient conditions, it was decided to introduce a rather unrealistically large step increase of about 40 per cent in the feed rate. In real life, most columns usually operate within 10 to 15 per cent of their full capacities and, therefore, step changes of more than 10 per cent are not expected or, if expected, they are usually buffered by a storage tank that precedes the column. However, it was thought to be necessary to test the simulator under extreme conditions to ensure its robustness. The experimental and simulation procedures were much the same as the steady-state case except that having run the column at steady state for 15 minutes, the feed rate is increased and an estimate of the time taken for the disturbance to reach the column is also made. This is important in

that this time lag must be allowed for in the simulation of the upset.

A typical set of the dynamic experimental results have been superimposed on their corresponding theoretical predictions and shown in Figures V.12 and V.13. The experimental details are given in Table V.1.

It was found necessary to use the Manchester Regional Computer for the simulation of the experiments since it was decided that the fourth-order Runge-Kutta integration method should be used to enhance the computational accuracy. The accuracy of the simulation predictions under transient conditions were also found to be in the order of  $\pm 0.6^{\circ}\text{C}$  as regards the topmost and lowermost tray temperatures.

Figure V.10  
Comparison of the Experimental and Predicted Steady-State  
Tray Temperatures

PLATE NUMBER= 1.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 25.00  
REFLUX TEMPERATURE= 30.000  
REFLUX RATE = 8.200

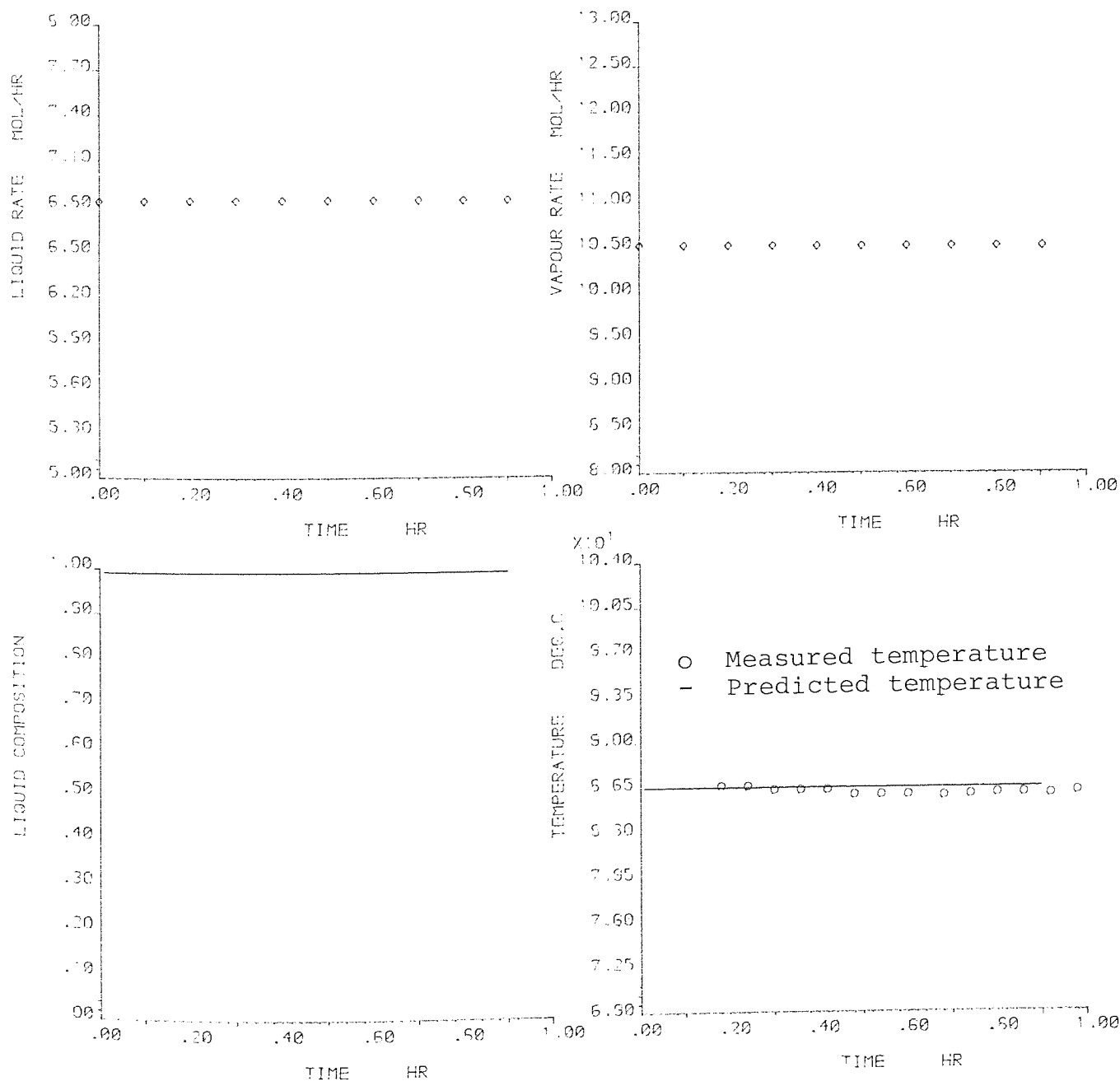


Figure V.11  
Steady-State Comparison Continued

PLATE NUMBER= 10.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 25.00  
REFLUX TEMPERATURE= 30.000  
REFLUX RATE = 8.200

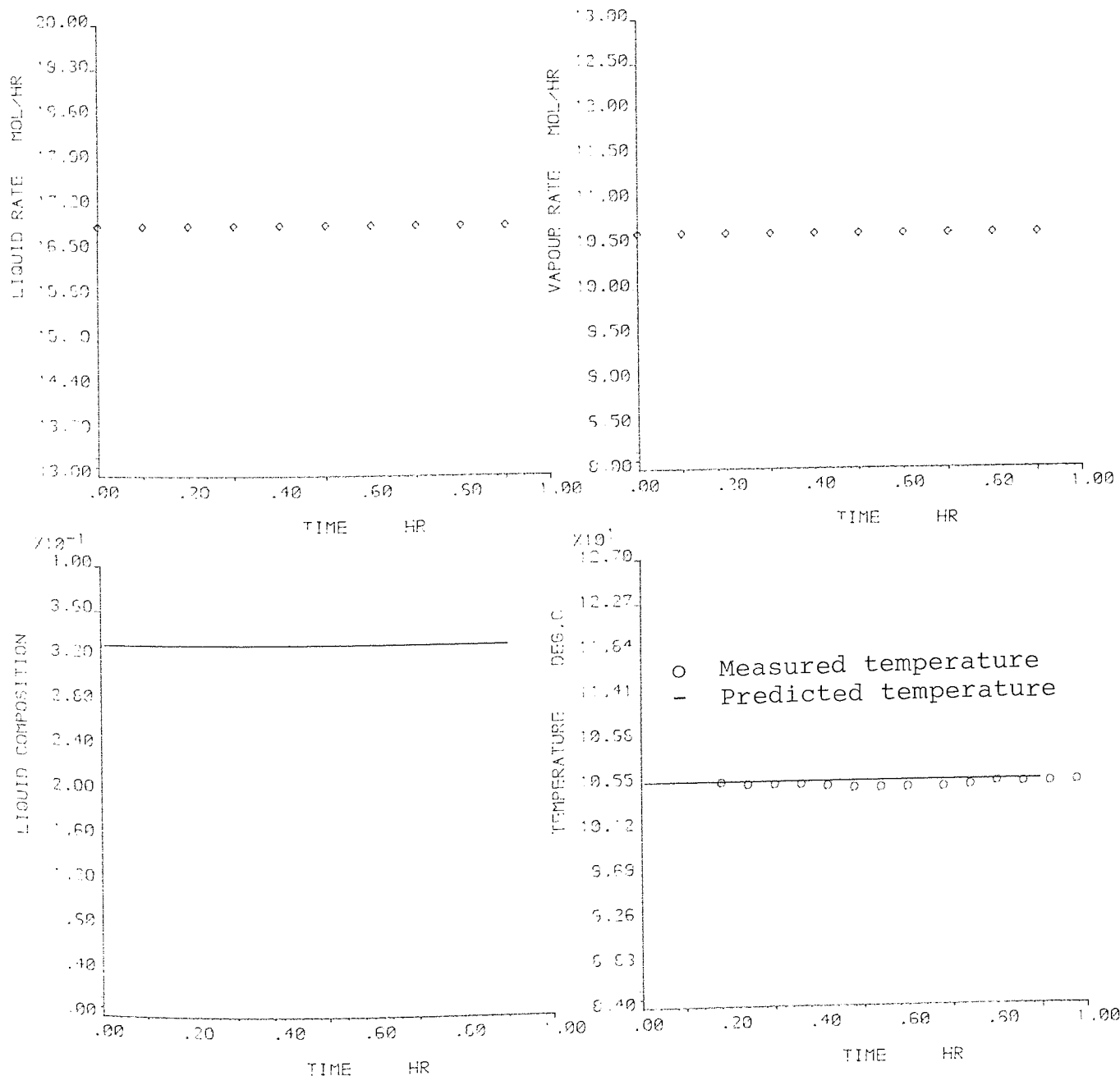


Figure V.12

Comparison of the Experimental and Predicted Open-Loop  
Tray Temperature Responses to 42% Step Increase in the  
Feed Rate

PLATE NUMBER= 1.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 23.00  
REFLUX TEMPERATURE= 33.000  
REFLUX RATE = 8.200

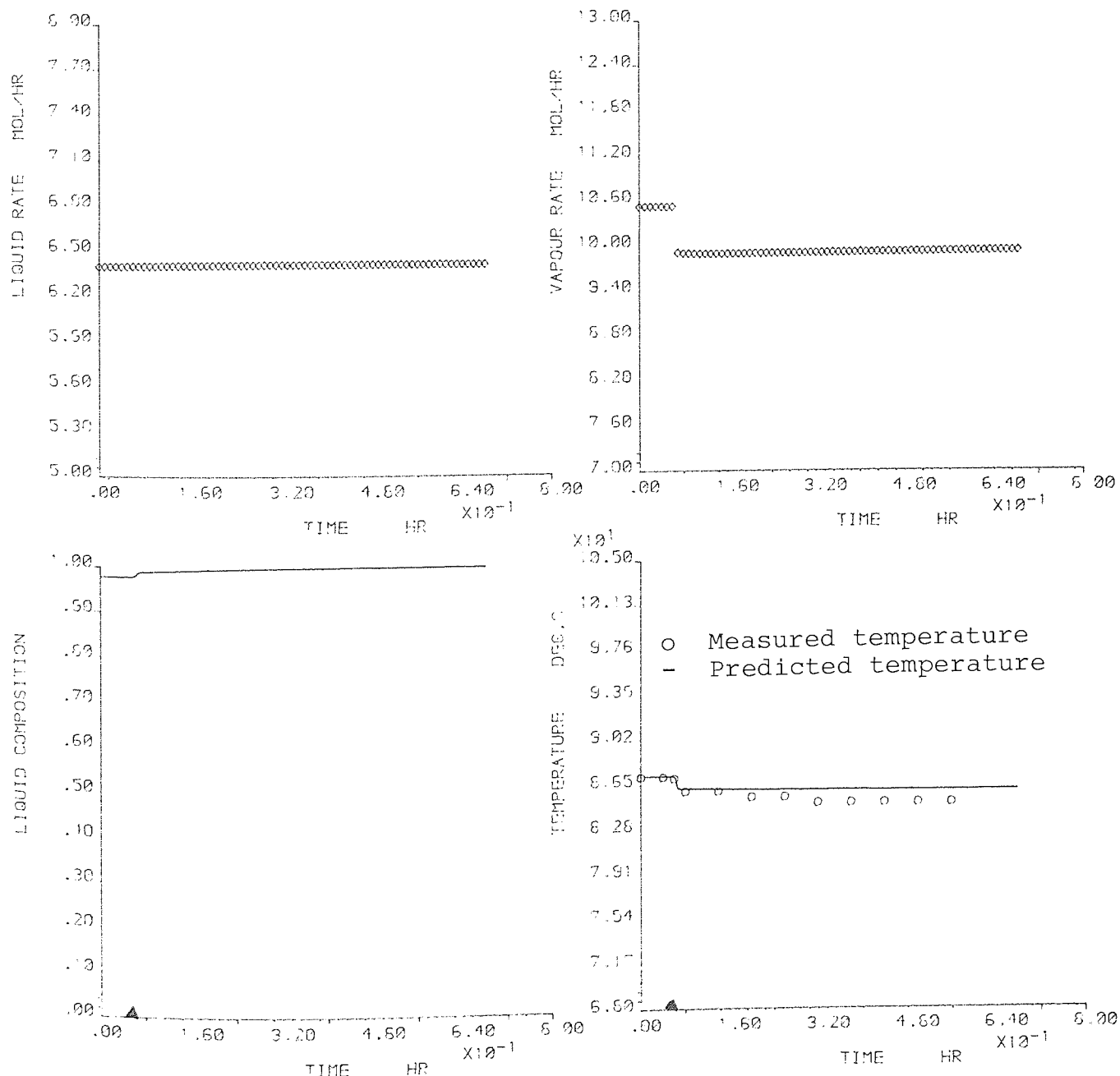
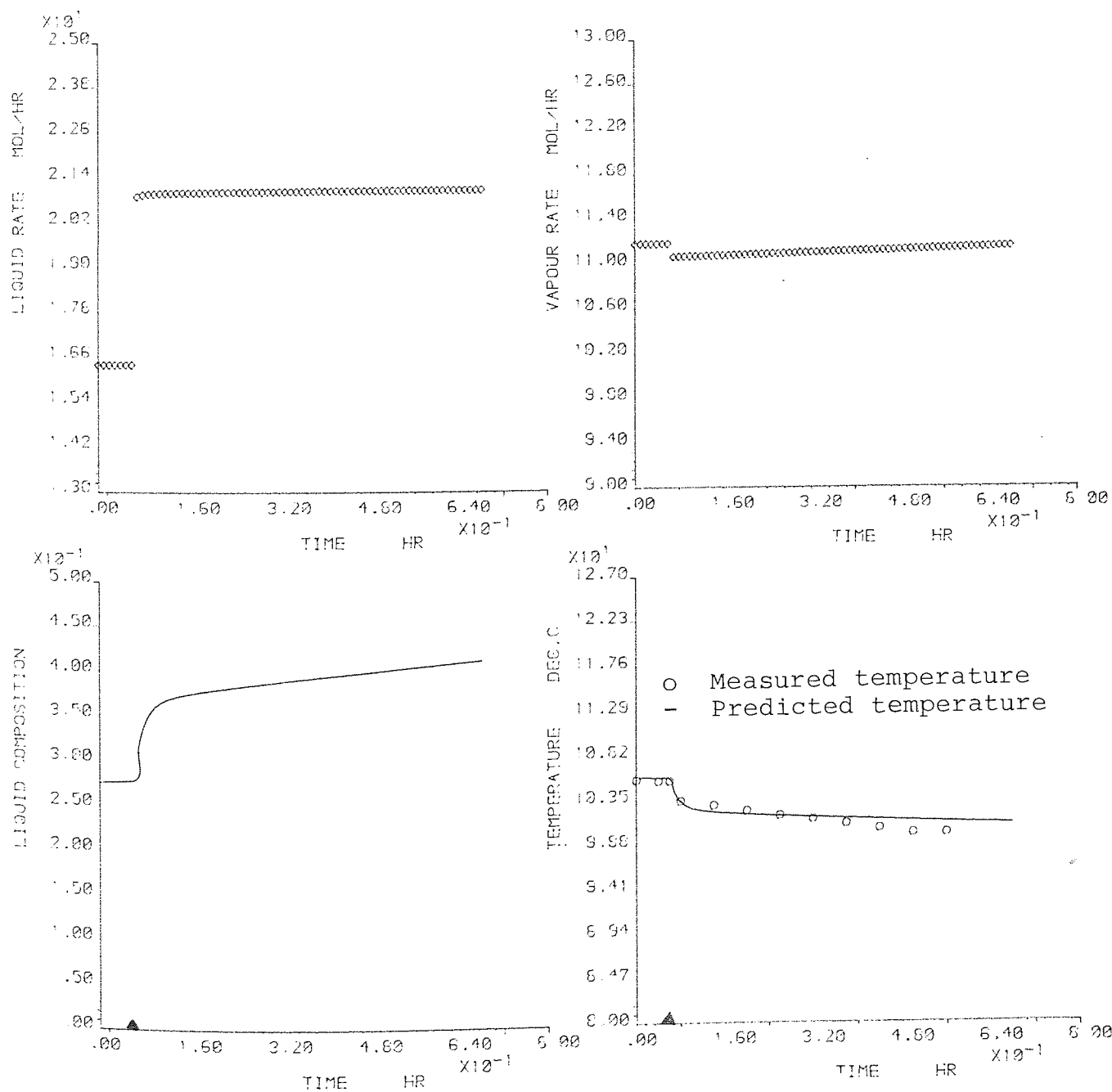




Figure V.13

Open-Loop Experimental and Predicted Responses of the Column  
to a 42% Step Increase in the Feed Rate Continued

PLATE NUMBER= 10.0  
FEED COMPOSITION= .400  
FEED TEMPERATURE= 23.00  
REFLUX TEMPERATURE= 23.000  
REFLUX RATE = 8.200



### Steady State Experimental Details

Feed rate	= 100	mole/hr.
Reflux rate	= 82	mole/hr.
Reboiler Holdup	= 100	moles
Reflux Drum Level	= 60	moles
Feed Composition	= 0.40	
Feed Temperature	= 25	°C
Reflux Temperature	= 30	°C
Actual Heat Input	= 4805	kJ./hr.
Estimated Heat Losses	= 1195	kJ./hr.
Scanning Interval	= 2.0	sec.

### Unsteady State Experimental Details

Feed Rate	= 100	moles/hr.
Reflux Rate	= 82	moles/hr.
Reboiler Holdup	= 100	moles
Reflux Drum Holdup	= 60	moles
Feed Composition	= 0.4	
Feed Temperature	= 27	°C
Reflux Temperature	= 33	°C
Actual Heat Input	= 4805	kJ./hr.
Estimated Heat Losses	= 1195	kJ./hr.
Size of the Step Change	= 0.42	
Scanning Interval	= 2.0	sec.

Table V.1 - The Experimental Details of the Steady-State Experiment No.5 and the Unsteady State Experiment No.7, are tabulated

C H A P T E R   S I X

THE DESIGN OF ESTIMATORS  
AND THEORETICAL DEVELOPMENTS

## VI.1 THE NEED FOR STOCHASTIC MODELS AND ESTIMATION IN RELATION TO CONTROL

There are several reasons for the use of stochastic models and estimation as an aid to control in the Chemical Process systems.

- (i) the limitations of deterministic models
- (ii) unknown system inputs
- (iii) imprecise measurements and the lack of availability and infrequency of primary control measurements

These points will now be discussed briefly.

### 1. The Limitations of Deterministic Models

Given a physical system which is to be controlled, an engineer attempts to develop a mathematical model of the system that adequately represents some aspects of the behaviour of that system. This is usually done by delineating the variables describing the process and then connecting them via certain causal relationships or physical laws. At this stage, such factors as physical insights, empirical testing can be instrumental in establishing the inter-relationships among certain variables of interest, inputs to the system and outputs from the system.

With such a mathematical model and the tools provided by system and control theories, it is then possible to investigate the system structure and modes of response and design controllers that provide

appropriate inputs to generate system responses - i.e. a control strategy.

On the implementation of this strategy on the real system, it is very likely that the system will not behave as expected due to inaccuracies in the mathematical model. Here, one might choose to sophisticate the model further and further in return for more accurate representations. There will, however, come a time when nothing more can be gained by further deterministic sophistications. This level of sophistication is normally identified as the "noise level". It can be confidently asserted that even at levels approaching the noise level, no deterministic mathematical model is perfect. If the mathematical model of the system is not as good as it can be, then the control strategy cannot as effective as it can be.

This provides the first incentive for resorting to stochastic models.

## 2. Unknown System Inputs

For the sake of argument, let us suppose that it is possible to achieve a perfect system model deterministically and the engineer then proceeds to design a controller based on this model. Almost invariably, the controller synthesis will then be based on pre-selected deterministic inputs. In actuality, real systems are not only driven by our own control inputs, but also by disturbances which we can neither control nor model deterministically. Thus, in the unlikely

event of achieving such a perfect deterministic model, the devised control strategy may still not be good enough.

### 3. Imprecise Measurements

Implicit in the control of any system is the need for some information about the system. This information can only be achieved by measuring some of the variables of the system. The variables that can be measured may suffer from the following disadvantages:

- (i) they may be corrupted as sensors do not provide perfect and complete data
- (ii) they may not be what we want to measure

Generally, sensors do not provide all the information that we would like to know : either a device cannot be devised to generate a measurement of a desired variable or the cost of including such a measurement is prohibitive. In other situations, a number of different devices yield functionally related data, and one must then ask how to generate a best estimate of the variables of interest based on partially redundant data. Not only do the sensors not provide exact readings, but also they introduce their own system dynamics and distortions. Furthermore, these devices are almost invariably noise corrupted. Imprecise measurement means imprecise control and one way to refine noisy measurements is by stochastic estimation.



A good example of how control is complicated by the problems associated with the on-line measurement of a tray composition occurs in distillation. On-line analysers are expensive and/or include such large time lags that makes it difficult to design even a reasonably effective feedback control system. Here an estimator can be used to estimate the tray composition from a secondary measurement such as tray temperature which is easy to measure. Control can then be based on this estimated composition.

## VI.2 THE KALMAN FILTER

The concept of Kalman filtering has already been introduced briefly in section II.4.1. The method of implementation of filtering philosophy in on-line and off-line applications is depicted in Figure VI.1.

A Kalman filter is simply an optimal recursive data processing algorithm. There are many ways of defining optimal, dependent upon the criteria chosen to evaluate performance. It can be shown (137), that under the assumptions made in the formulation of the Kalman filter, the filter is optimal with respect to virtually any criterion that makes sense. One aspect of this optimality is that the Kalman filter incorporates all information that can be provided to it. It processes all available measurements, regardless of their precision, to estimate the current values of the variables of interest with the use of

- (i) knowledge of the system and measurement dynamics (filter model(s))
- (ii) the statistical description of the system noises, measurement errors, and the uncertainty in the dynamics models ( $R$  and  $Q$  matrices)
- (iii) any available information about initial conditions of the variables of interest ( $\bar{x}(t_0)$  and  $P(0,0)$ )

The word "recursive" means that the Kalman filter does not require all previous data to be kept in

storage and reprocessed every time a new measurement is taken. This is of vital importance to the practicality of filter implementation on digital computers.

The basic assumptions made in the Kalman filter formulation are:

- (i) a linear system model
- (ii) whiteness of the noise
- (iii) Gaussian distribution of the noise

The use of a linear model is not restrictive. If non-linearities do exist, the typical engineering approach is to linearize about some nominal point or trajectory to achieve a perturbation or error model (see the extended Kalman filter). There are also means of developing non-linear filters (16).

"Whiteness" implies that the noise value is not correlated in time. As a result the knowledge of the value of the noise now in no way helps in predicting its value at any other time. In other words, all the values of the noise are "mutually independent".

Whereas Whiteness pertains to time or frequency relationship of noise, "Gaussianness" is related to its amplitude. Thus, at any single point in time, the probability density of a Gaussian noise amplitude takes on the shape of a normal bell-shaped curve. This assumption can be justified physically by the fact that a system measurement noise is typically caused by a number of small sources. It can be shown mathematically that when a number of independent

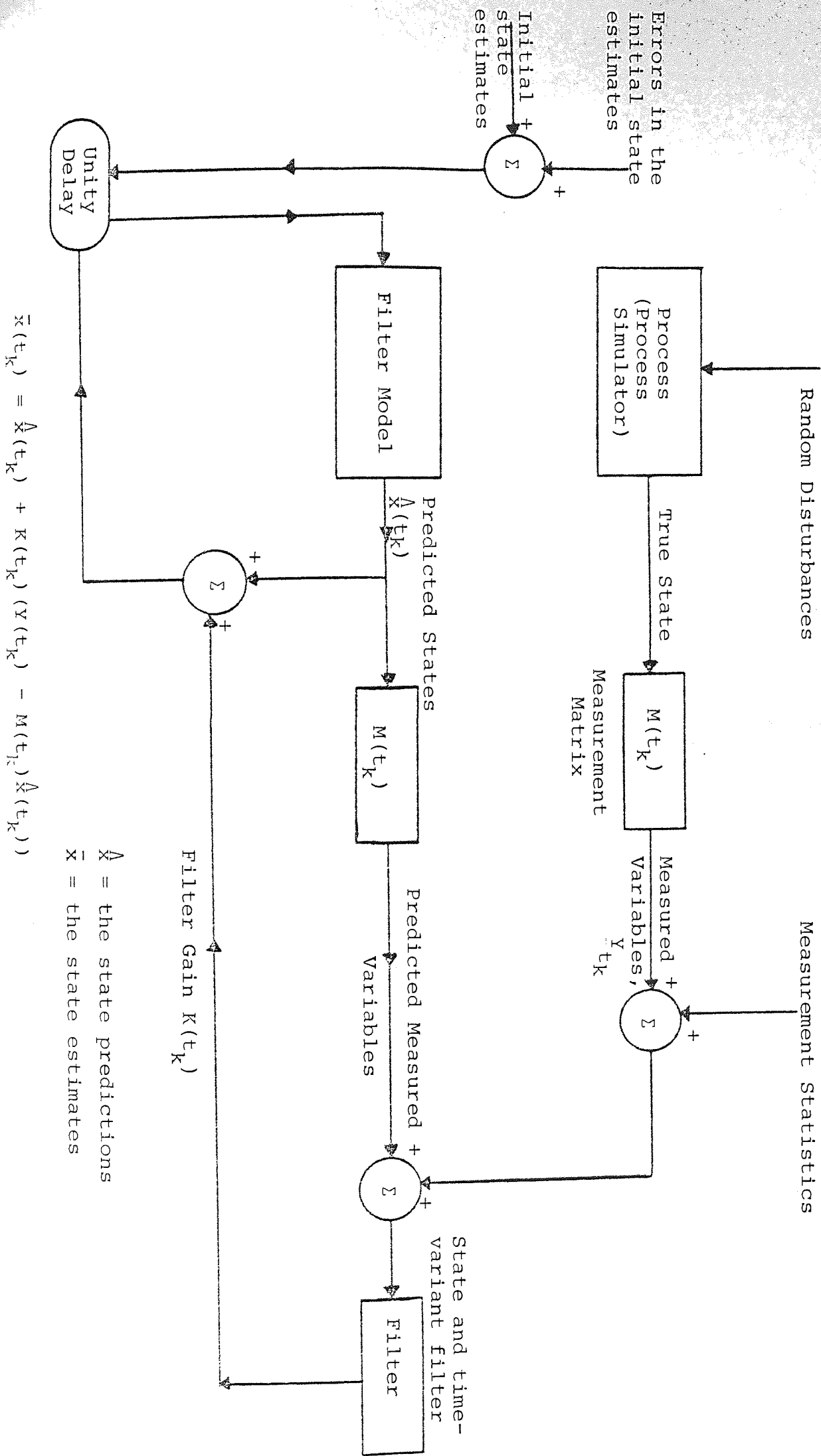
random variables are added together, the summed effect can be described very closely by a Gaussian probability density, regardless of the shape of the individual densities.

The practical justifications for using a "White Gaussian" noise in stochastic models are:

- (i) it makes the mathematics more tractable
- (ii) it is completely defined by its first and second order statistics

Therefore, in describing a dynamical system stochastically, almost invariably, it pays to adhere to the White Gaussian noise processes.

FIGURE VI.1 - Estimation Procedure in On-line and Off-line Applications



### V1.3 THE DESIGN OF KALMAN FILTERS

Despite the mathematical formalism of the Kalman filter approach, a substantial amount of engineering insight and experience is required to develop an effective operational filter. Mathematical models of both the system structure (state dynamics and output relations) and uncertainties are inherently embodied in the Kalman filter structure. However, obtaining an "adequate mathematical model upon which to base the filter" is the crux of the design problem. Even once a particular model is chosen as appropriate for a given application, a considerable effort may still be needed to obtain appropriate numerical evaluation of the coefficients within the model - especially the covariance matrices. This process will henceforth be referred to as "filter tuning". It essentially involves an iterative search for the coefficient values that yeild the optimum estimation performance from a particular filter structure.

Moreover, the design must meet the constraints of the on-line computer time, memory and wordlength available. These considerations dictate a philosophy of using as simple a filter as possible that yields adequate results. Consequently, it might be that one is forced to exploit basic modelling alternatives to achieve a simple but adequate filter. Modelling complexities might have to be added or deleted as the performance needs and practical constraints require.



Evaluation of true performance capabilities of any filter is of critical importance in the design procedure. Although a Kalman filter computes an error covariance internally, this is a valid depiction of the true errors committed by the filter only to the extent that the filter's own system model adequately portrays the true system behaviour. It is possible for the filter not to perform as well as it "thinks" it does. If the computed error covariance matrix is inappropriately small, the computed gain will also be small. This means that the filter weights its internal system model too heavily and disregards the data from the "real world" unduly. This phenomenon will lead to filter estimates not corresponding to the true system performance with a simultaneous indication by the filter through its computed covariance that all is well. Usually, under these circumstances the filter exhibits some peculiar behaviour. For instance, if the inaccuracies of the filter's system model are not properly allowed for, the estimates may diverge gradually or the filter may fail to track the estimated parameters if any.

It is generally felt that evaluation of the true performance of any Kalman filter is best accomplished by simulation. This is the reason why simulation is regarded as being an important preliminary to the design of Kalman filters.

#### VI.4 OBSERVABILITY

Observability is a property of a specific state space representation for a system, rather than of the system itself. Thus certain state space models will be more suitable for estimation than others, even though both might portray the input-output characteristics of the system.

The concept of observability in linear systems is well established and the methods available for assessing observability are generally applicable (137). However, in non-linear systems, although this concept has been considered by many workers, some of whom have tried to quantify observability, there are, as yet, no general methods of assessing observability. Experience has, however, shown that this is one issue which has to be settled at the simulation stage of designing a Kalman filter and one obvious way to combat unobservability is to increase the number of measured variables. Experience has also shown that the system becomes unobservable when some of the estimates oscillate about the true states and the related diagonal elements in the computed error covariance matrix,  $P_{n,n}$ , become unduly large - larger than the corresponding state variables themselves in some cases. For example, if a state variable happens to be a mole fraction which can only have a maximum value of 1 and its computed variance is 2, then its estimate will be somewhat meaningless.

## VI.5 THE COVARIANCE MATRICES : Q AND R

The error covariance matrices  $Q$  and  $R$  are not computed by the filter algorithm and must, therefore, be specified. In specifying the  $Q$  and  $R$  matrices, one can initially assume that the cross-correlation coefficients are small compared to the auto correlation coefficients so that only the diagonal terms are significant in the covariance matrices. These diagonal terms correspond to the expected variances in the state and measured variables. Subsequently, cross correlations can be allowed for if, and where, expected.

Changing the  $Q$  or the  $R$  matrices in the filter does affect the filter operation considerably. Increasing  $Q$  would indicate either stronger noise driving the dynamics or increased uncertainty in the adequacy of the filter model itself to show the true dynamics accurately. This will increase the rate of growth of the elements of the  $P$  matrix. As a result, the filter gain will generally increase, thereby weighing the measurements more heavily. This is to be expected since increased  $Q$  implies that one is placing less confidence in the output of the filter's own dynamics model. By similar reasoning, increased  $R$  would indicate that the measurements are subjected to a stronger corruptive noise, and so should be weighted less by the filter. This means that the filter treats the measurements with greater reservation.

"Filter Tuning" essentially means that we have to find the reasonable values of the  $Q$  and  $R$  matrices for an effective operational filter.

## VI.6 THE EXTENDED KALMAN FILTER

As mentioned in section II.4.3, most of the engineering problems are non-linear and must be linearized before the linear filter theory can be applied. Supposing that the non-linear system is described by

$$dx_t = F(x_t, u_t)dt + G(t)d\beta_t \dots\dots\dots \text{VI.1}$$

with discrete measurements

$$y(t_k) = h(x(t_k)) + v_{t_k} \dots\dots\dots \text{VI.2}$$

where the symbols are as defined in section II.4.3.

Now consider the deterministic reference trajectory  $\bar{x}_t$  and a nominal value of  $u_t$  called  $\bar{u}_t$  which satisfies

$$d\bar{x}_t = F(\bar{x}_t, \bar{u}_t)dt \dots\dots\dots \text{VI.3}$$

Define:

$$\delta x_t \triangleq x_t - \bar{x}_t \quad \text{and} \quad \delta u_t = u_t - \bar{u}_t \dots\dots\dots \text{VI.4}$$

i.e. the deviations from the reference trajectory.

We can see that  $\delta x_t$  is a stochastic process satisfying the differential equation

$$d(\delta x_t) = \{F(x_t, u_t) - F(\bar{x}_t, \bar{u}_t)\}dt + G(t)d\beta_t \dots\dots\dots \text{VI.5}$$



If the deviations from the reference trajectory are "small", then a Taylor series expansion gives

$$F(x_t, u_t) - F(\bar{x}_t, \bar{u}_t) \approx A(\bar{x}_t, \bar{u}_t) \cdot \delta x_t + D(\bar{x}_t, \bar{u}_t) \cdot \delta u_t$$

..... VI.6

where

$$A(\bar{x}_t, \bar{u}_t) = \left. \frac{\partial F_i(x_t, u_t)}{\partial x_j} \right|_{\bar{x}_t, \bar{u}_t}$$

..... VI.7

$$D(\bar{x}_t, \bar{u}_t) = \left. \frac{\partial F_i(x_t, u_t)}{\partial u_j} \right|_{\bar{x}_t, \bar{u}_t}$$

..... VI.8

Substituting from VI.6 into VI.5 we get

$$d(\delta x_t) = A(\bar{x}_t, \bar{u}_t) \delta x_t \cdot dt + D(\bar{x}_t, \bar{u}_t) \delta u_t \cdot dt + G(t) d\beta_t$$

..... VI.9

After integration and assuming that the deterministic system inputs are time-invariant between  $t_k$  and  $t_{k+1}$  (piecewise constant), equation VI.9 can be discretised as before

$$\delta x(t_{k+1}) = \Phi(t_{k+1}, t_k) \delta x(t_k) + \Gamma_D(t_k) \delta u(t_k) + \Gamma(t_k) w_{t_{k+1}}$$

..... VI.10

where  $\Phi$  is usual state transition matrix and the rest of the symbols are as defined in section II.4.1.

By the same procedure, the measurement equation can be linearized about  $\bar{x}_t$  to give



$$\delta y(t_k) = M(\bar{x}_t) \delta x(t_k) + v_{t_k} \dots\dots\dots \text{VI.11}$$

where

$$M(\bar{x}_t) = \left. \frac{\partial h_1(x(t_k))}{\partial x_j} \right|_{\bar{x}_t}$$

To summarize the linearized equations are:

$$\delta x(t_{k+1}) = \Phi(t_{k+1}, t_k) \delta x(t_k) + \Gamma_D(t_k) \delta u(t_k) + \Gamma(t_k) w_{t_{k+1}} \dots\dots\dots \text{VI.12}$$

$$\delta y(t_k) = M(\bar{x}_t) \delta x(t_k) + v_{t_k} \dots\dots\dots \text{VI.13}$$

It can be seen that the linear filtering algorithm introduced in section II.4.1 is directly applicable provided that the state and measured variables are replaced by the "deviations" from a reference trajectory. Given a reference trajectory and measurements  $y(t_k)$ , we can then compute  $\delta y(t_k)$  and process the measurement deviations through the linear filter to estimate the state deviations and then back calculate the actual state estimates.

The remaining problems are the choice of the reference trajectory and the question of the validity of the linearized equations. The obvious choice of the reference trajectory at time  $t_0$  is a priori estimate of the state. However, if the estimate is not as accurate as it should be (if  $p(0,0)$  or  $Q$  is large), then the estimates of the state deviations can become large, violating the linearity assumption. In the case of a poor a priori estimate of state, it

may be worthwhile to use an iterative approach to improve on it. This means that having processed the first batch of the measurements and computed the first estimates of the state one can then predict backward to  $t_0$  using

$$\delta \hat{x}(t_0, t_k) = \Phi(t_0, t_k) \delta \hat{x}(t_0, t_k) + \Gamma_D(t_k) \delta \hat{u}(t_k) \dots\dots\dots \text{VI.14}$$

Thus

$$\bar{x}'(t_0) = \bar{x}(t_0) + \delta \hat{x}(t_0, t_k) \dots\dots\dots \text{VI.15}$$

If the processed batch of measurements is sufficiently large, we can expect  $\bar{x}'(t_0)$  to be closer to the "true" state than  $\bar{x}(t_0)$ . This procedure can be repeated several times until no further improvement is achieved.

As an alternative, since the linear filter has a recursive structure, one can go a step further and relinearize about each last estimate as it becomes available. In other words, the reference trajectory is not fixed any longer and a better reference trajectory is used as soon as it becomes available. By this sequence of relinearization large initial estimation errors are not allowed to propagate through time and, therefore, the linearity assumptions are less likely to be violated. Here the prediction stage is accomplished by the integration of the non-linear system differential equations with the noise term equal to zero.

Some authors (16), have argued that by a sequence of relinearization one is able to process the actual

state and measured variables as opposed to the "deviations". In practice, this is possible if the measurement relationship is linear or very mildly non-linear.

Notation:

$x_t$	continuous variable
$x(t_k)$	discrete variable
$x_k$ and $x(k)$	abriviations for $x(t_k)$
$t$	continuous time
$t_k$	discrete time
$\bar{x}$	the estimated value of $x$
$\hat{x}$	the predicted value of $x$

## VI.7 PARAMETER ESTIMATION

Frequently, in applications, the dynamical system depends upon certain parameters whose values are imprecisely known. These parameters may be treated as pseudo state variables whose differential equations are equal to zero and thus estimated. The implication of this is that one is effectively treating the parameters as random variables and thus their a priori statistics needs to be known.

Each estimated parameter increases the dimensionality of the filter and thus the computational load. On the other hand better accuracy may result if more parameters are estimated. Therefore, some trade-off may be necessary between the number of estimated parameters and the accuracy of estimation.

An alternative approach is to take into account the effect of the parameters in degrading the estimates of the state, without estimating the parameters themselves as in the Schmidt-Kalman filter (16). However, this means that the actual filter algorithm has to be modified and thus will not be adopted in this research since it also increases the dimensionality of the filter which may not be justifiable for distillation.



## VI.8 THE STATE TRANSITION MATRIX $\Phi$

### (a) Linear Systems

Consider the linear, time-varying, continuous-time system of stochastic differential equations:

$$dx_t = A(t)x_t dt + D(t)u_t dt + G(t).d\beta_t \dots \text{VI.16}$$

with initial conditions  $x(t_0) = x_0$

Assuming  $A(t)$  and  $D(t)u_t$  are piecewise continuous, the solution to this equation is

$$x_t = \Phi(t, t_0)x_{t_0} + \int_{t_0}^t \Phi(t, \tau)D(\tau)u_\tau d\tau + \int_{t_0}^t \Phi(t, \tau)G(\tau).d\beta_\tau$$

..... VI.17

where  $\Phi$  is the state transition matrix defined by

$$\frac{d\Phi(t, t_0)}{dt} = A(t)\Phi(t, t_0) \dots \text{VI.18}$$

Significant properties of the state transition matrix include:

- (i)  $\Phi(t, \tau)$  is uniquely defined for all  $t$  and  $\tau$  in  $(0, \infty)$
- (ii) the semigroup property i.e.  
 $\Phi(t, \xi) = \Phi(t, \tau)\Phi(\tau, \xi)$  for all  $t, \tau$  and  $\xi$
- (iii)  $\Phi(t, \tau)$  is non-singular and invertible:  
 $\Phi^{-1}(t, \tau) = \Phi(\tau, t)$

The discrete-time "equivalent" of this continuous-time model would have a solution similar to equation VI.17 with  $t$  replaced with  $t_k$

$$\Phi(t_{k+1}) = \Phi(t_{k+1}, t_k) x(t_k) + \int_{t_k}^{t_{k+1}} \Phi(t_{k+1}, \tau) D(\tau) u_\tau d\tau + \int_{t_k}^{t_{k+1}} \Phi(t_{k+1}, \tau) G(\tau) d\beta$$

..... VI.19

with the state transition matrix defined as for the continuous-time system.

The two systems are "equivalent" in the sense that the discrete-time model values  $x(t_1), x(t_2), \dots$ , are identical to those of the continuous-time at these particular times.

Schwarz and Friedland(139) by integration of equation VI.18 deduce that

$$\Phi(t, t_0) = \exp\left(\int_{t_0}^t A(\tau) d\tau\right) \dots\dots\dots \text{VI.20}$$

Unfortunately, however, this relation is not valid unless  $A(t)$  and  $\int_{t_0}^t A(\tau) d\tau$  commute. One such case occurs when the matrix  $A(t)$  is the product of a constant matrix and a scalar time function, i.e.

$$\underline{A}(t) = g(t)\underline{k}$$

In this case:  $\Phi(t, t_0) = \exp\left(\int_{t_0}^t \underline{A}(\tau) d\tau\right) = \exp\left(\underline{k} \int_{t_0}^t g(\tau) d\tau\right)$

..... VI.21

Amundson(140) shows that equation VI.18 can be integrated by repeated substitution to give



$$\begin{aligned} \phi(t, t_0) = I + \int_{t_0}^t A(t_1) dt_1 + \int_{t_0}^t A(t_1) dt_1 \int_{t_0}^t A(t_2) dt_2 + \\ \int_{t_0}^t A(t_1) dt_1 \int_{t_0}^t A(t_2) dt_2 \int_{t_0}^t A(t_3) dt_3 + \dots \end{aligned}$$

..... VI.22

Again, this integration can only be performed under special circumstances. Therefore, it remains to conclude that the evaluation of  $\phi$  in the general sense is impossible in practice.

However, if the system of differential equations is assumed to be time-invariant ( $A$  is a constant matrix), then the associated  $\phi(t, t_0)$  could be characterized further. If  $A$  is a constant matrix, then the associated  $\phi(t, t_0)$  is not a function of the separate arguments  $t$  and  $t_0$  but a function only of a single parameter  $(t - t_0)$ . Thus the general defining relationship for  $\phi$  reduces to

$$\frac{d}{dt} \phi(t - t_0) = A \phi(t - t_0); \quad \phi(0) = I \dots \dots \dots \text{VI.23}$$

to which the solution can be expressed as the matrix exponential

$$\phi(t, t_0) = \phi(t - t_0) = \exp(A \delta t); \quad \delta t = t - t_0 \dots \text{VI.24}$$

Similarly for the discrete time-model.

(b) Non-linear Systems

If the linear filter algorithm is to be applied to non-linear systems the golden rule to be followed is not to violate the linearity assumption. As shown in section VI.6, a non-linear system of stochastic differential equations can be linearized to give

$$d(\delta x_t) = A(\bar{x}_t, \bar{u}_t) \delta x_t . dt + D(\bar{x}_t, \bar{u}_t) \delta u_t . dt + G(t) . d\beta_t$$

This system is identical to the linear system provided that state and measurement "deviations" are processed in the filter algorithm and the deviations are kept "small". This means that the dynamic behaviour of the non-linear system is approximated by a linear system over the time interval  $\delta t$ . Thus the linear filter algorithm is applicable provided that  $\delta t$  and thus  $\delta x$  and  $\delta u$  which are implicit functions of time are "small" enough not to violate the linearity assumption.

The state transition matrix for this linearized system can now be evaluated as if it were a linear system. Once again to make the evaluation possible, in practice, one has to assume that the system is time-invariant over the time interval  $\delta t$ . However, this assumption is likely to be more restrictive now. Because, if the prediction stage in the linear filter algorithm is accomplished using this approximate state transition matrix, the inaccuracies, resulting from linearization on the one hand and the assumption of

time-invariance on the other, may accumulate and violate the linearity assumption inherent in the linear filter algorithm and cause divergence. Thus it makes sense to try to avoid the use of  $\Phi$  as far as possible.  $\Phi$  appears in the prediction of  $x(t_{k+1})$  and the covariance matrix  $P$ . The prediction of  $x(t_{k+1})$  can be accomplished by the integration of the system of non-linear differential equations. As regards  $P$ , a similar approach can also be adopted in that the time propagation relation for  $p$  can be integrated. However, this integration can be cumbersome and lengthy, and, for this reason only, it is preferable to discretise the dynamics and compute  $P$  via  $\Phi$ .

## VI.9 PROPOSED ALGORITHM FOR THE IMPLEMENTATION OF EXTENDED KALMAN FILTERS

The following algorithm is believed to broaden the flexibility and horizons of extended Kalman filtering in process applications:

1. Set  $k=0$  : guess  $\bar{x}(t_k)$ ,  $\bar{u}(t_k)$ ,  $p(k,k)$  and thus  $\bar{y}(t_k)$ .
2. Compute  $\Phi$  based on  $\bar{x}(t_k)$ .
3. Predict  $\hat{x}(t_{k+1})$  by the integration of the non-linear differential equations (filter model) starting from  $\bar{x}(t_k)$ .

4. Compute the predicted state and measurement deviations using

$$\delta \hat{x}(t_{k+1}) = \hat{x}(t_{k+1}) - \bar{x}(t_k)$$

$$\delta y(t_{k+1}) = y(t_{k+1}) - \bar{y}(t_k)$$

5. Process the deviations through the linear filter algorithm introduced in Section II.4.2 and thus produce  $\delta \bar{x}(t_{k+1})$ .
6. Compute  $\bar{x}(t_{k+1})$  using  $\bar{x}(t_{k+1}) = \delta \bar{x}(t_{k+1}) + \bar{x}(t_k)$ .
7. Compute  $\bar{y}(t_{k+1})$  using the filter model or otherwise.
8. Set  $k=k+1$ , return to step 2 and continue.

## C H A P T E R   S E V E N

THE ESTIMATORS AND SIMULATED  
OPEN-LOOP ESTIMATION RESULTS



## VII.1 THE FILTERS FORMULATED

The extended Kalman filters formulated have the following common features:

- (i) use Model I discussed in Chapter IV as the filter's system model. It is worth noting that Model I is highly simplified and inaccurate compared with the column simulator model (Model II, Chapter IV).

- (ii) Compute the state transition matrix via

$$\Phi(k+1,k) = I + \frac{\partial f(x_k, u_k)}{\partial x_k} \cdot \delta t \dots\dots\dots \text{VII.1}$$

where  $\delta t$  is the sample time and the jacobian  $\frac{\partial f(x_k, u_k)}{\partial x_k}$  is evaluated about the latest estimated state

- (iii) a sample time of 18 seconds

- (iv) the initial estimate of the state is provided by an approximate McCabe-Thiele calculation

The estimation simulation studies are carried out using the process simulator (Model II, Chapter IV) which has already been shown to represent the dynamic and static characters of the distillation column with reasonable accuracy (see Chapter V). The filters formulated and the associated filter models are simply inserted into the simulator with the necessary channels for the inter-communications. The filtering philosophy is then implemented as depicted in Figure VI.1, while the algorithm given in Section VI.9 helps provide



better insight into the procedural completion of the various steps involved. The additional programs needed essentially include a library of matrix and vector manipulation routines and a subroutine for the initialization of the filter model. Once again the programs are largely self-documenting and the listings shown in Appendix E should provide enough information for the programs to be followed. Therefore, detailed discussion of the individual subroutines will be foregone. However, some elaboration on the main program arrangement may be in order at this stage.

## VII.2 FILTERING SIMULATION PACKAGE : THE MAIN PROGRAM

### SEGMENTS

The main segments of the simulation package for estimation are:

- SUBROUTINE INDATA - Read in the data required for the initialization of the column simulator based on Model II, plus the details of the deterministic disturbances to be introduced and P,R and Q matrices.
- SUBROUTINE HKEEP - Subroutine to calculate the Antoine and Van Laar constants.
- SUBROUTINE SDWEG - Subroutine to find the reflux ratio for a desired separation by Wegstein algorithm.
- SUBROUTINE SSMODL - Subroutine to perform McCabe-Thiele calculation for the initialization of the column simulator and filter model.
- SUBROUTINE GOFIL - Subroutine to initialize the column simulator and the filter model.
- SUBROUTINE LATEST - Subroutine to compute  $\phi$  and store the latest estimated state and measured variables.

SUBROUTINE DISCOL - The column simulator subroutine.

SUBROUTINE SIMUL - The filter model.

SUBROUTINE PRINT - Subroutine to print out variables of interest.

SUBROUTINE SDBUB - Bubble point calculation.

SUBROUTINE SDDEW - Dew point calculation.

SUBROUTINES SDINT, INTJS and INTPAS - Subroutines constituting the SDINT integrator.

SUBROUTINE EFF - Efficiency calculation.

SUBROUTINE MATINV - Matrix inversion by Gauss-Jordan elimination.

SUBROUTINE MATTPS - Matrix transposition.

SUBROUTINE MATMUL - Matrix multiplication.

SUBROUTINE MATADD - Matrix addition.

SUBROUTINE MATSUB - Matrix subtraction.

SUBROUTINE MATVEC - Matrix-vector multiplication.

SUBROUTINE VECADD - Vector addition.

SUBROUTINE VECSUB - Vector subtraction.

SUBROUTINE Kalman - The filter.

The package also contains a number of other sub-routines that essentially facilitate the communication with the package and whose listings should be self-explanatory (see Appendix E) (Microfiche).

The flow chart for the main program arrangement is shown in VII.1. The filters tested in this research are:

Extended Kalman Filter 1 (EKF1) : State estimation from  
noisy tray composition  
measurements.

Extended Kalman Filter 2 (EKF2) : State estimation  
from noisy tray  
temperature measurements.

Extended Kalman Filter 3 (EKF3) : State and parameter  
estimation from noisy  
tray temperature  
measurements.

These filters will now be described in more detail.

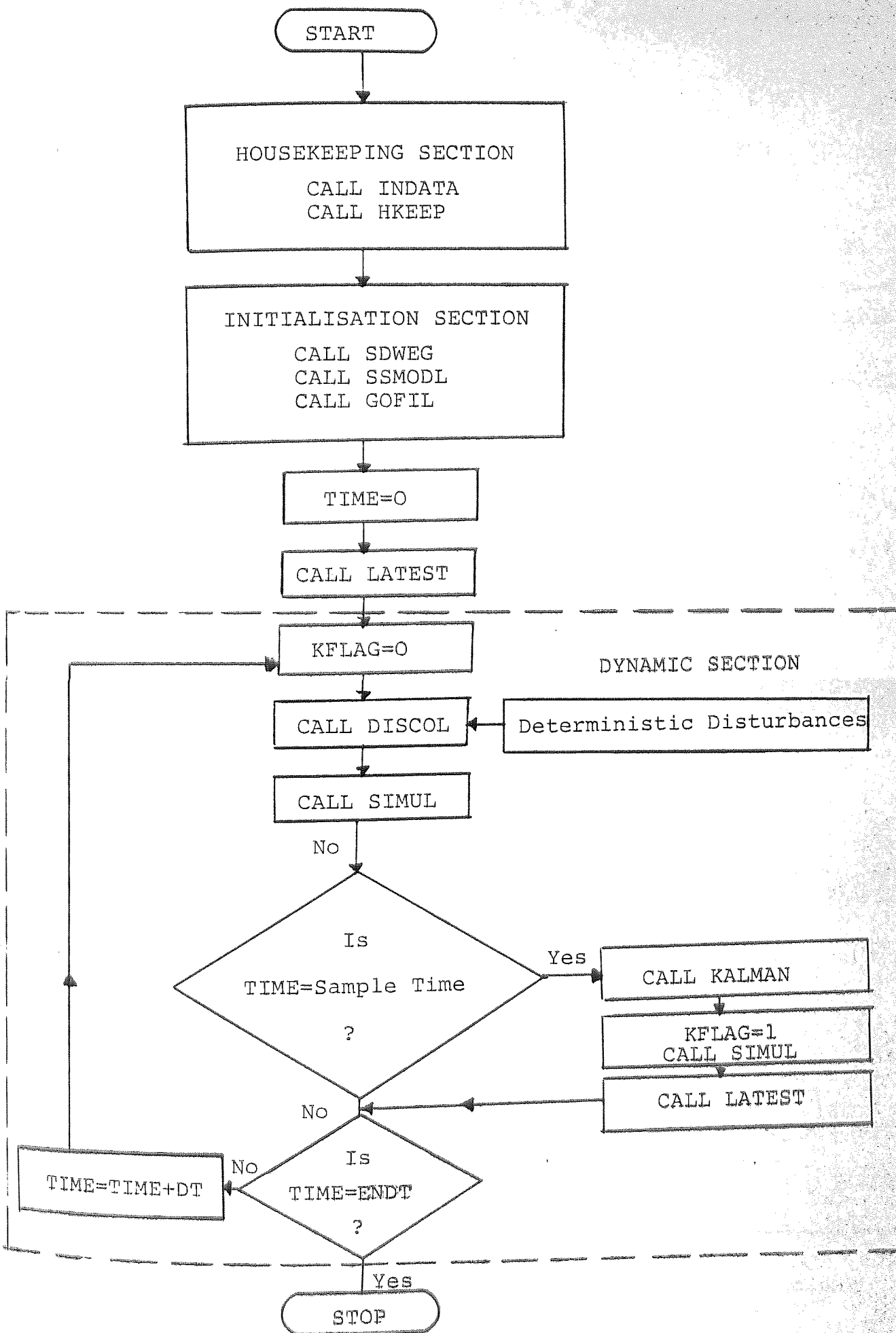


FIGURE VII.1 - The Main Program Arrangement for the  
Filtering Package  
N.B. If KFLAG=1, the filter model bypasses the Integration  
Section



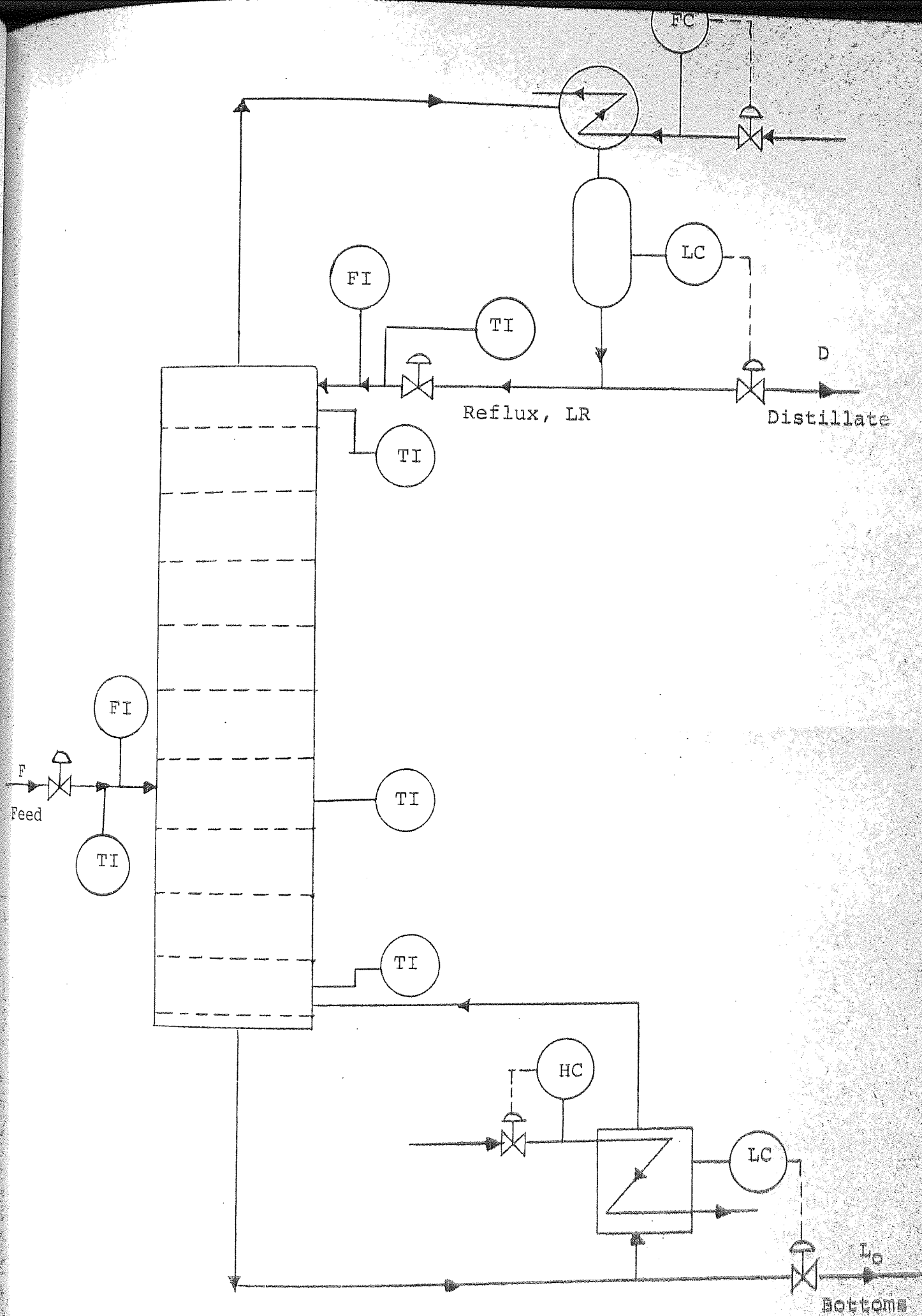


Figure VII.2 - The Symbolic Representation of the Column  
Used for Open-Loop Estimation



### VII.3 STATE ESTIMATION FROM NOISY COMPOSITION

#### MEASUREMENTS : EKf1

The symbolic representation of the column used for open-loop estimation is depicted in Figure VII.2.

#### VII.3.1 THE STATE VARIABLES

Since the symbol  $x$  is used to denote the state variables in the filter algorithm and also the mole fraction of the M.V.C. on the  $n$ th tray, the following notation will be used to avoid confusion:

$x_j$  denotes the state variables

$x_n$  denotes the mole fraction of the M.V.C. on the  $n$ th tray

$M_n$  denotes the liquid holdup on the  $n$ th tray

i.e. variables subscripted by  $n$  refer to the mole fractions and those subscripted by  $j$  denote the state variables.

The elements of the state vector are:

$$x_j = x_n \quad j = 1,11; n = 1,11$$

$$x_j = M_n \quad j = 11,22; n = 1,11$$

### VII.3.2 THE STATE TRANSITION MATRIX (22-by-22)

In equation VII.1 the Jacobian  $\frac{\partial f(x_k, u_k)}{\partial x_k}$  will henceforth be abbreviated to  $\frac{\partial f}{\partial x}$  for convenience of notation.  $\frac{\partial f}{\partial x}$  is defined as

$$\frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_m} \\ \vdots & & \vdots \\ \frac{\partial f_m}{\partial x_1} & \dots & \frac{\partial f_m}{\partial x_m} \end{bmatrix} \dots \text{VII.2}$$

where

$$f_1 = \frac{L_R(x_D - x_1) + v(y_2 - y_1)}{M_1}$$

$$f_i = \frac{L_{i-1}(x_{i-1} - x_i) + v(y_{i+1} - y_i)}{M_i} ; i=2,6$$

$$f_7 = \frac{L_6(x_6 - x_7) + v(y_8 - y_7) + F(x_F - x_7)}{M_7}$$

$$f_i = \frac{L_{i-1}(x_{i-1} - x_i) + v(y_{i+1} - y_i)}{M_i} ; i=8,10$$

$$f_{11} = \frac{L_{10}(x_{10} - x_{11}) + v(x_{11} - y_{11})}{M_{11}}$$

$$f_{12} = L_R - L_1$$

$$f_i = L_{i-11} - L_{i-12} ; i=13,17$$

N.B. During the partial differentiation of  $f_i (i=1,11)$  with respect to the liquid composition, for simplicity, the functional relationship between  $y_i$  and  $x_i (i=1,11)$  has been ignored. This may be considered as a modelling error and from reported experience the filters should be insensitive to these types of errors. Had this functional relationship been included, the corresponding elements of the state transition matrix would have been modified as illustrated in Appendix G.

$$f_{18} = L_6 - L_7 + F$$

$$f_i = L_{i-11} - L_{i-12}; \quad i=19,21$$

$$f_{22} = L_{10} - L_{11} - v$$

The rows of the Jacobian can now be calculated as follows:

First Row

$$\frac{\partial f_1}{\partial x_1} = - \frac{L_R}{M_1}$$

$$\frac{\partial f_j}{\partial x_j} = 0; \quad j=2,11$$

$$\frac{\partial f_1}{\partial x_{12}} = \frac{-\{L_R(x_D - x_1) + v(y_2 - y_1)\}}{(M_1)^2}$$

$$\frac{\partial f_1}{\partial x_j} = 0; \quad j=13,22$$

Second Row

$$\frac{\partial f_2}{\partial x_1} = \frac{L_1}{M_2}$$

$$\frac{\partial f_2}{\partial x_2} = - \frac{L_1}{M_2}$$

$$\frac{\partial f_2}{\partial x_j} = 0; \quad j=3,12$$

$$\frac{\partial f_2}{\partial x_{13}} = \frac{-\{L_1(x_1-x_2) + v(y_3-y_2)\}}{(M_2)^2}$$

$$\frac{\partial f_2}{\partial x_j} = 0; \quad j=14,22$$

### Third Row

$$\frac{\partial f_3}{\partial x_1} = 0$$

$$\frac{\partial f_3}{\partial x_2} = \frac{L_2}{M_3}$$

$$\frac{\partial f_3}{\partial x_3} = -\frac{L_2}{M_3}$$

$$\frac{\partial f_3}{\partial x_j} = 0; \quad j=4,13$$

$$\frac{\partial f_3}{\partial x_{14}} = \frac{-\{L_2(x_2-x_3) + v(y_4-y_3)\}}{(M_3)^2}$$

$$\frac{\partial f_3}{\partial x_j} = 0; \quad j=15,22$$

### Fourth Row

$$\frac{\partial f_4}{\partial x_j} = 0; \quad j=1,2$$

$$\frac{\partial f_4}{\partial x_3} = \frac{L_3}{M_4}$$

$$\frac{\partial f_4}{\partial x_4} = -\frac{L_3}{M_4}$$

$$\frac{\partial f_6}{\partial x_j} = 0; \quad j=7,16$$

$$\frac{\partial f_6}{\partial x_{17}} = \frac{-\{L_5(x_5-x_6) + v(y_7-y_6)\}}{(M_6)^2}$$

$$\frac{\partial f_6}{\partial x_j} = 0; \quad j=18,22$$

#### Seventh Row

$$\frac{\partial f_7}{\partial x_j} = 0; \quad j=1,5$$

$$\frac{\partial f_7}{\partial x_6} = \frac{L_6}{M_7}$$

$$\frac{\partial f_7}{\partial x_7} = -\frac{(L_6+F)}{M_7}$$

$$\frac{\partial f_7}{\partial x_j} = 0; \quad j=8,17$$

$$\frac{\partial f_7}{\partial x_{18}} = \frac{-\{L_6(x_6-x_7) + v(y_8-y_7) + F(x_F-x_7)\}}{(M_7)^2}$$

$$\frac{\partial f_7}{\partial x_j} = 0; \quad j=19,22$$

#### Eighth Row

$$\frac{\partial f_8}{\partial x_j} = 0; \quad j=1,6$$

$$\frac{\partial f_8}{\partial x_7} = \frac{L_7}{M_8}$$



$$\frac{\partial f_8}{\partial x_8} = - \frac{L_7}{M_8}$$

$$\frac{\partial f_8}{\partial x_j} = 0; \quad j=9,18$$

$$\frac{\partial f_8}{\partial x_{19}} = \frac{-\{L_7(x_7-x_8) + v(y_8-y_7)\}}{(M_8)^2}$$

$$\frac{\partial f_8}{\partial x_j} = 0; \quad j=20,22$$

#### Ninth Row

$$\frac{\partial f_9}{\partial x_j} = 0; \quad j=1,7$$

$$\frac{\partial f_9}{\partial x_8} = \frac{L_8}{M_9}$$

$$\frac{\partial f_9}{\partial x_9} = - \frac{L_8}{M_9}$$

$$\frac{\partial f_9}{\partial x_j} = 0; \quad j=10,19$$

$$\frac{\partial f_9}{\partial x_{20}} = \frac{-\{L_8(x_8-x_9) + v(y_{10}-y_9)\}}{(M_9)^2}$$

$$\frac{\partial f_9}{\partial x_j} = 0; \quad j=21,22$$

Tenth Row

$$\frac{\partial f_{10}}{\partial x_j} = 0; \quad j=1,8$$

$$\frac{\partial f_{10}}{\partial x_9} = \frac{L_9}{M_{10}}$$

$$\frac{\partial f_{10}}{\partial x_{10}} = -\frac{L_9}{M_{10}}$$

$$\frac{\partial f_{10}}{\partial x_j} = 0; \quad j=11,20$$

$$\frac{\partial f_{10}}{\partial x_{21}} = \frac{-\{L_9(x_9 - x_{10}) + v(y_{11} - y_{10})\}}{(M_{10})^2}$$

$$\frac{\partial f_{10}}{\partial x_{22}} = 0$$

Eleventh Row

$$\frac{\partial f_{11}}{\partial x_j} = 0; \quad j=1,9$$

$$\frac{\partial f_{11}}{\partial x_{10}} = \frac{L_{10}}{M_{11}}$$

$$\frac{\partial f_{11}}{\partial x_{11}} = \frac{-L_{10} + v}{M_{11}}$$

$$\frac{\partial f_{11}}{\partial x_j} = 0; \quad j=12,21$$

$$\frac{\partial f_{11}}{\partial x_{22}} = \frac{-\{L_{10}(x_{10} - x_{11}) + v(x_{11} - y_{11})\}}{(M_{11})^2}$$

### Twelfth to Twenty Second Rows

$$\frac{\partial f_i}{\partial x_j} = 0; \quad i=12,22; \quad j=1,22$$

Thus having computed the Jacobian, the calculation of  $\Phi$  is a mere formality.

### VII.3.3 THE MEASUREMENT VECTOR (3-by-1)

Assuming three composition measurements are available, the measurement vector donated by  $y$  consists of:

$y_1 = x_1$  : liquid composition on the topmost tray

$y_2 = x_7$  : liquid composition on the feed tray

$y_3 = x_{10}$  : liquid composition on the lowermost tray

### VII.3.4 THE MEASUREMENT MATRIX (3-by-22)

The elements of the measurement matrix are all zero except:

$$M(1,1) = 1.0$$

$$M(2,7) = 1.0$$

$$M(3,10) = 1.0$$

### VII.3.5 THE MEASUREMENT NOISE MATRIX (3-by-3)

The non-diagonal elements of this matrix are zero. The diagonal elements were chosen to be:

$$R = \text{diag.} \{0.003 \quad 0.003 \quad 0.003\}$$

This means that the standard deviation of the composition measurements is 5.4%.

### VII.3.6 THE SYSTEM NOISE MATRIX (22-by-22)

The non-diagonal elements of this matrix are also zero. The diagonal elements were all selected as 0.003 which is the average expected value obtained by comparison of the predictions of Model I (the filter model) with Model II (the column simulator model) in Chapter V, i.e.

$$Q = \text{diag.} \{0.003 \quad \dots \quad 0.003\}$$

### VII.3.7 THE INITIAL ERROR COVARIANCE MATRIX (22-by-22)

The non-diagonal elements of the  $P(0,0)$  matrix are set to zero. The diagonal elements are all equal to 0.001, i.e.

$$P(0,0) = \text{diag.} \{0.001 \quad \dots \quad 0.001\}$$

This means that the standard deviation of the initial composition estimates is 3.1% while that of the holdups is 31%. i.e. we have less confidence in our initial estimates of the holdups.

### VII.3.8 THE INITIAL ESTIMATE OF THE STATE

This is calculated internally by the simulator by a McCabe-Thiele calculation for the separation

$$F = 10 \quad \text{mole/hr.}$$

$$x_F = 0.4$$

$$x_D = 0.91$$

$$x_B = 0.09$$

$$R = 2.0$$

Having calculated the compositions and the rates, the tray hold-ups are then calculated internally using the truncated Brambilla correlation.

#### VII.3.9 THE SIMULATED MEASUREMENT NOISE

The composition measurements were corrupted by a white Gaussian noise characterized by  $(0, \sqrt{0.003})$  which was added to the composition measurements.

#### VII.3.10 THE SIMULATION RESULTS USING EKFL

The simulation studies in Chapter V show that starting from an approximate steady-state predicted by the McCabe-Thiele's method, the column simulator undergoes a transient period to reach a more accurate steady-state. The state estimates produced by EKFL during this transient period continued to track the actual state through to the refined steady-state with excellent accuracy. The maximum estimation error as regards the tray compositions was in the order of 0.004 and much less for the holdups. Even when step

disturbances were introduced into the column at steady-state which were "unknown" to the filter and its model, the estimates still continued to track the actual states with a comparable accuracy. The following "unknown" disturbances were studied in this context:

- (i) 10% step changes in the feed rate and composition
- (ii) 10% step changes in the boilup and reflux rates
- (iii) 10% step changes in the feed and reflux stream temperatures

In all these case studies, the filter showed no difficulty in producing accurate estimates of the tray compositions and holdups. It was then decided to use simple Euler for the integration of the filter model equations while the column simulator used the fourth-order Runge-Kutta with the same step size and the sample time was increased to 36 seconds. Here, again, the filter exhibited no difficulty in estimating the tray compositions and holdups. This can be a valuable feature because it can reduce the calculation cycle time considerably and the advantage of being able to increase the sample time is always desirable - especially in high dimensionality systems.

Another interesting feature of EKFl was that, with a sample time of 18 seconds only, it was possible to process the actual state and measured variables through the filter as opposed to the deviations from the latest estimated trajectory. This is because the



measurement functional relationship is linear and the filter is apparently capable of coping with the nonlinearities due to the system model with a small sample time.

It remains to conclude that the simulation studies using EKFl were sufficiently encouraging to proceed to explore the additional capabilities of the extended Kalman filter in application to distillation columns.

## VII.4 STATE ESTIMATION FROM NOISY TRAY TEMPERATURE

### MEASUREMENTS : EKF2

The state vector and the state transition matrix for this filter are identical to the EKF1.

#### VII.4.1 THE MEASUREMENT VECTOR (3-by-1)

The measurement vector consists of:

$y_1 = T_1$  : the topmost tray temperature

$y_2 = T_7$  : the feed tray temperature

$y_3 = T_{10}$  : the lowermost tray temperature

#### VII.4.2 THE MEASUREMENT MATRIX (3-by-22)

Since the state variables are not being measured directly, a functional relationship is needed to relate the measured variables to the state variables, i.e.  $T = g(x)$ . Moreover, this function has to be continuous and differentiable. For a binary mixture it can be shown that on each tray

$$x_1 = \frac{P - P_2^O(T)}{P_1^O(T) - P_2^O(T)} \dots\dots\dots \text{VII.2}$$

Using the following physical laws:

(i) Raoult's law :  $x_i P_i^O(T) = P_i$

(ii) Dalton's law :  $P_i = y_i P$

(iii) Antoine's equation :  $\log P_i^O(T) = A_i - \frac{B_i}{C_i + T}$

where

$x_i, y_i$  = liquid and vapour mole fractions of component i

$p_i$  = partial pressure of component i (mm. Hg.)

$p_i^O(T)$  = vapour pressure of i (mm. Hg.)

$P$  = total system pressure (mm. Hg.)

For convenience of differentiation since  $T$  is a function of  $x$  only in this particular case we can write

$$\frac{\partial T}{\partial x} = \frac{1}{\frac{\partial x}{\partial T}} = \frac{\{P_1^O(T) - P_2^O(T)\}^2}{-\frac{\partial P_2^O}{\partial T}\{P_1^O(T) - P_2^O(T)\} - \left\{\frac{\partial P_1^O(T)}{\partial T} - \frac{\partial P_2^O(T)}{\partial T}\right\}\{P - P_2^O(T)\}}$$

..... VII.3

where

$$\frac{\partial P_i^O(T)}{\partial T} = \frac{2.303B_i}{(C_i + T)^2} P_i(T)$$

The measurement matrix is therefore a matrix of zero elements except

$$M(1,1) = \frac{\partial T_1}{\partial x_1}$$

$$M(2,7) = \frac{\partial T_7}{\partial x_7}$$

$$M(3,10) = \frac{\partial T_{10}}{\partial x_{10}}$$

#### VII.4.3 THE MEASUREMENT NOISE MATRIX (3-by-3)

$$R = \text{diag.}\{0.01 \quad 0.01 \quad 0.01\}$$

The figure 0.01 is, in actuality, the expected variance about the regression plane of one of the thermocouples on the column.

#### VII.4.4 THE SYSTEM NOISE MATRIX (22-by-22)

The diagonal elements of  $Q$  were found by trial and error starting from the average expected variance 0.003, obtained by comparison of Models I and II, in Chapter V.

$$Q = \text{diag.}\{0.006, 0.009, 0.009, 0.09, 0.09, 0.006 \dots 0.006\}$$

#### VII.4.5 THE INITIAL ERROR COVARIANCE MATRIX : 22-by-22

This is the same as EKFI

$$P(0,0) = \text{diag.}\{0.001 \dots \dots \dots 0.001\}$$

#### VII.4.6 THE INITIAL ESTIMATE OF THE STATE

This is calculated in a similar manner to EKFI.

#### VII.4.7 THE SIMULATED MEASUREMENT NOISE

The temperature measurements are corrupted by a white Gaussian sequence characterized by  $(0, \sqrt{0.01})$  which is added to the temperature measurements. Notice that the size of the noise should not exceed what we have allowed for through the  $R$  matrix.

## VII.5 STATE AND PARAMETER ESTIMATION FROM NOISY TRAY TEMPERATURE MEASUREMENTS: EKF3

The system inputs which are of primary importance in the study of dynamics and control of binary distillation columns are namely:

- (i) the feed rate :  $F$
- (ii) the feed composition :  $x_F$
- (iii) the reflux rate :  $L_R$
- (iv) the boilup rate :  $v$

Admittedly other inputs could also be considered. However, since every estimated input increases the dimensionality of the filter and thus the inter-sample computational load, each input must be selected judiciously according to its merits and influence on the predictions of the filter model. As regards binary distillation columns, it is difficult to justify other inputs outside the ones listed above. The EKF3 estimates these inputs by treating them as pseudo state variables with their differential equations equal to zero.

### VII.5.1 THE STATE VECTOR (26-by-1)

The first 24 elements of the state vector are the same as EKF1. The last 4 elements are

$$\begin{array}{ll} x_{23} = F & x_{25} = v \\ x_{24} = x_F & x_{26} = L_R \end{array}$$

## VII.5.2 THE STATE TRANSITION MATRIX (26-by-26)

The Jacobian in the state transition matrix is much the same as EKF1 except for the following additional non-zero elements which correspond to the additional four pseudo state variables in the state vector.

### First Row

$$\frac{\partial f_1}{\partial x_{25}} = \frac{Y_2 - Y_1}{M_1}$$

$$\frac{\partial f_1}{\partial x_{26}} = \frac{x_D - x_1}{M_1}$$

### Second Row

$$\frac{\partial f_2}{\partial x_{25}} = \frac{Y_3 - Y_2}{M_2}$$

### Third Row

$$\frac{\partial f_3}{\partial x_{25}} = \frac{Y_4 - Y_3}{M_3}$$

### Fourth Row

$$\frac{\partial f_4}{\partial x_{25}} = \frac{Y_5 - Y_4}{M_4}$$

### Fifth Row

$$\frac{\partial f_5}{\partial x_{25}} = \frac{Y_6 - Y_5}{M_5}$$



Sixth Row

$$\frac{\partial f_6}{\partial x_{25}} = \frac{y_7 - y_6}{M_6}$$

Seventh Row

$$\frac{\partial f_7}{\partial x_{23}} = \frac{x_F - x_7}{M_7}$$

$$\frac{\partial f_7}{\partial x_{24}} = \frac{F}{M_7}$$

$$\frac{\partial f_7}{\partial x_{25}} = \frac{y_8 - y_7}{M_7}$$

Eighth Row

$$\frac{\partial f_8}{\partial x_{25}} = \frac{y_9 - y_8}{M_8}$$

Ninth Row

$$\frac{\partial f_9}{\partial x_{25}} = \frac{y_{10} - y_9}{M_9}$$

Tenth Row

$$\frac{\partial f_{10}}{\partial x_{25}} = \frac{y_{11} - y_{10}}{M_{10}}$$

Eleventh Row

$$\frac{\partial f_{11}}{\partial x_{25}} = \frac{x_{11} - y_{11}}{M_{11}}$$

Twelfth Row

$$\frac{\partial f_{12}}{\partial x_{26}} = 1.0$$

#### Eighteenth Row

$$\frac{\partial f_{18}}{\partial x_{23}} = 1.0$$

#### Twenty Second Row

$$\frac{\partial f_{22}}{\partial x_{25}} = -1.0$$

#### VII.5.3 THE MEASUREMENT VECTOR (5-by-1)

Since flow rate measurements can be assumed to be readily available, EKF3 expects the feed and reflux rates as measured variables. This is essentially to prevent the system from becoming unobservable which may stem from the attempted identification of a high dimensionality system from a handful of three temperature measurements. Therefore, the measurement vector consists of

$y_1 = T_1$  : the topmost tray temperature

$y_2 = T_7$  : the feed tray temperature

$y_3 = T_{10}$  : the lowermost tray temperature

$y_4 = F$  : the feed rate

$y_5 = LR$  : the reflux rate

#### VII.5.4 THE MEASUREMENT MATRIX (5-by-26)

As in EKF2 we can write  $x = g(T)$  and hence obtain  $\frac{\partial T}{\partial x}$  on each tray. Thus, the elements of the measurement

matrix are all zero except

$$M(1,1) = \frac{\partial T_1}{\partial x_1}$$

$$M(2,7) = \frac{\partial T_7}{\partial x_7}$$

$$M(3,10) = \frac{\partial T_{10}}{\partial x_{10}}$$

$$M(4,23) = 1.0$$

$$M(5,26) = 1.0$$

#### VII.5.5 THE MEASUREMENT NOISE MATRIX (5-by-5)

$$R = \text{diag.}\{0.01 \quad 0.01 \quad 0.01 \quad 1.0 \quad 1.0\}$$

Notice this means that the standard deviation of the feed rate measurement is 10% and that of the reflux measurement is about 16%.

#### VII.5.6 THE SYSTEM NOISE MATRIX (26-by-26)

Once again the diagonal elements of Q were found by trial and error.

$$Q = \text{diag.}\{0.006, 0.009, 0.009, 0.09, 0.09, 0.006 \dots 1.0,$$

$$0.15, 1.0, 1.0\}$$

#### VII.5.7 THE INITIAL ERROR COVARIANCE MATRIX (26-by-26)

$$P(0,0) = \begin{bmatrix} 0.001 & \dots & 0.04 & 0.04 & 0.04 & 0.04 \end{bmatrix}$$

#### VII.5.8 THE INITIAL ESTIMATE OF THE STATE

This is computed in a similar manner to EKFl.

#### VII.5.9 SIMULATED MEASUREMENT NOISE

The temperature measurements are corrupted by a white Gaussian sequence characterized by  $(0, \sqrt{0.01})$ . The feed rate measurement is corrupted by  $(0.25, \sqrt{0.5})$  or  $(0, \sqrt{0.5})$  and the reflux measurement is corrupted by  $(0, \sqrt{0.4})$

## VII.6 THE SIMULATION RESULTS USING EKF3

The graphical presentation of the simulation results using EKF3 will now follow. The deterministic disturbances of both known and unknown natures which were introduced simultaneously after the column had reached steady state (0.5 hrs) were:

- (i) multiple step changes in the feed rate which is available to the filter as a highly corrupted measured variable (see Figure VII.8)
- (ii) a ramp change followed by multiple step changes in the feed composition which is supplied to the filter as a parameter to be estimated (see Figure VII.9)
- (iii) a step increase of  $10^{\circ}\text{C}$  in the feed temperature which is unknown to the filter

The steady-state filter gain is given in Table VII.1. The sample time used was 18 seconds. This filter was also tested using a sample time of 36 seconds and using simple Euler for predictions while the column simulator was being integrated by the fourth-order Runge-Kutta method - the step sizes being the same. Under these conditions and with the same input disturbances as described above, the filter was stable and the estimation was almost equally accurate.

### VII.6.1 OBSERVATIONS FROM THE STEADY-STATE FILTER

#### GAIN MATRIX : TABLE VII.1

The filter gains at the measurement points have been marked by \*. It can be seen that the filter pays more attention to the state variables whose associated temperatures are being measured. The composition estimates (rows 1-11) and the boilup rate (element (25,3)) which is estimated as a pseudo state variable, benefit more from the temperature measurements than the flow measurements. It is significant that the tray holdup estimates are also weighted towards the temperature measurements except on trays 1 and 7 where feed and reflux streams enter the column (see the underlined elements). Since these are available to the filter as measured parameters which are to be estimated, the filter takes their respective measurements more into account. This is a good example of how state estimation can benefit from more estimated parameters.

### VII.6.2 REMARKS ON THE ESTIMATION RESULTS

Figure VII.3:

The simulated actual and estimated liquid compositions on tray 1 where a corrupt temperature measurement is taken. The picture is slightly distorted because the plotter attempts to fit



a curve to the points. Nevertheless the estimates show remarkable agreement with the actual values.

Figure VII.4:

An example of the simulated actual and estimated liquid compositions on a tray in the enriching section where there is no measurement. The estimates are still very accurate.

Figure VII.5:

Simulated actual and estimated liquid compositions on the feed tray where a corrupt temperature measurement is taken. The points are joined by straight lines. A good demonstration of the accuracy of the estimates.

Figure VII.6:

Simulated actual and estimated liquid compositions on a tray in the stripping section where there is no temperature measurement. By contrast with plate 4, the estimates on this plate show relatively closer agreement with the actual values. This is because there are more temperature measurements in the stripping section than the enriching section.

Figure VII.7:

Simulated actual and estimated bottoms composition. There is little variation in the actual composition because of the excessively large reboiler holdup. The estimates are again accurate.

Figure VII.8:

Simulated multiple step changes in the feed rate which is supplied to the filter as a noisy measurement and the estimates produced. Although non-zero mean noise has been deliberately added to the measurements which effectively acts as a bias, the filter still tracks the development of the actual value. It is significant that although the filter is not troubled by this bias globally in that the state estimates are accurate, it is unable to remove the bias locally. i.e. the estimates of the feed rate have a distinct positive bias. This is to be expected since this type of Kalman filter is not geared to remove biases (39).

Figure VII.9:

Simulated changes in the feed composition which is available to the filter as an unmeasured parameter to be estimated. Once again there is a distinct positive bias in the estimates. It is possible that this is due to the filter

being unable to remove the bias in the feed flow rate estimates. Biases can also stem from nonlinearities which can arise at the feed point in a distillation column.

* -.4542E-01	-.5006E-08	-.1638E-06	-.1340E-10	.5363E-06
-.8364E-04	.1259E-05	-.1800E-03	-.7204E-08	-.2679E-06
-.8027E-04	-.8630E-04	-.4521E-03	-.2246E-06	-.4454E-06
-.1299E-03	-.1585E-02	-.7517E-03	-.3861E-05	-.7102E-06
-.1834E-03	-.5569E-02	-.1084E-02	-.1405E-04	-.1003E-05
-.2417E-03	-.3241E-02	-.1440E-02	-.1043E-04	-.1322E-05
-.3963E-08	* -.3607E-01	-.1428E-07	.1711E-07	-.1768E-10
-.1218E-03	-.3771E-04	-.2726E-03	-.8032E-07	-.6301E-06
-.3266E-03	-.3586E-04	-.1741E-02	-.1165E-06	-.1723E-05
-.9426E-07	-.1038E-07	* -.2622E-01	-.3001E-10	-.5033E-09
-.1444E-04	-.3879E-07	-.9029E-04	-.6740E-09	-.7885E-07
<u>-.5435E-02</u>	-.1138E-05	.2022E-03	-.1753E-08	<u>.1864E-02</u>
-.1317E-05	-.2405E-03	-.8538E-05	-.3721E-06	-.7449E-08
.1076E-06	-.3086E-04	.5649E-06	-.9750E-07	.5773E-09
.6365E-07	-.6614E-04	.3076E-06	-.1463E-06	.3210E-09
.3994E-06	-.3117E-03	.1756E-05	-.7694E-06	.2025E-08
-.1326E-06	.1267E-03	.2323E-06	.7073E-06	-.5121E-09
-.1658E-06	<u>-.4079E-02</u>	-.4626E-05	<u>.1902E-02</u>	-.2837E-08
-.8018E-05	.5120E-05	-.3571E-02	.1356E-07	-.5974E-07
-.5531E-04	.2049E-05	-.5688E-02	.3333E-09	-.3318E-06
.1834E-03	.3026E-04	-.1944E-01	.8038E-07	.9429E-06
-.9097E-03	.8772E-05	-.5790E-02	-.1168E-07	-.4949E-05
.2940E-07	-.4742E-04	.1144E-06	* .5180	.1390E-09
.2400E-03	-.6392E-01	.1365E-02	-.1739E-03	.1292E-05
.2468E-01	.3785E-02	.1244	.1013E-04	.1278E-03
-.1177E-02	.4900E-07	.1919E-05	.1390E-09	* .6180

Table VII.1  
The Steady-State Filter Gain for EKF3

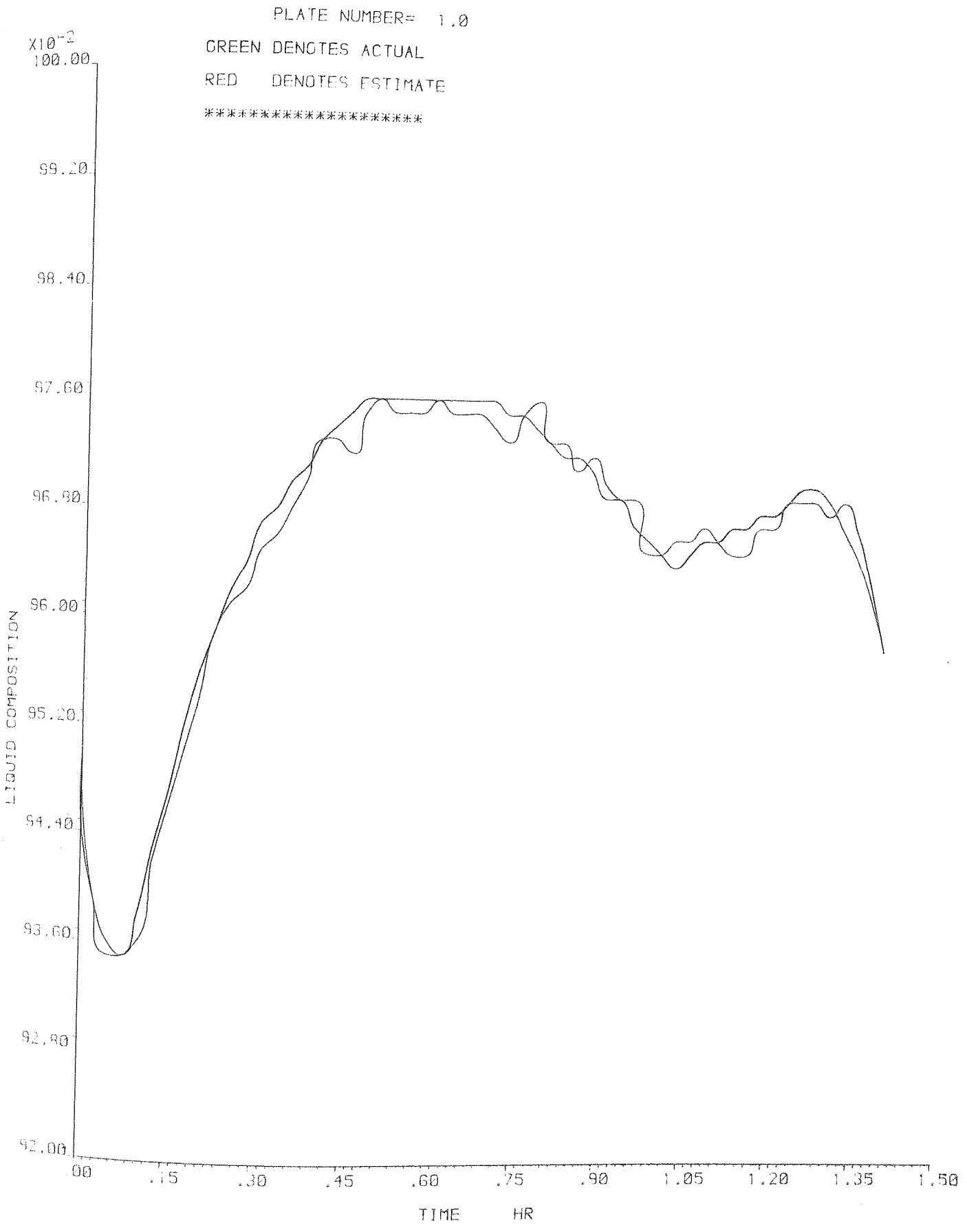


Figure VII.3  
Simulated actual and estimated liquid compositions on tray 1  
where a corrupt temperature measurement is taken

-259-

PLATE NUMBER- 4.0

GREEN DENOTES ACTUAL

RED DENOTES ESTIMATE

\*\*\*\*\*

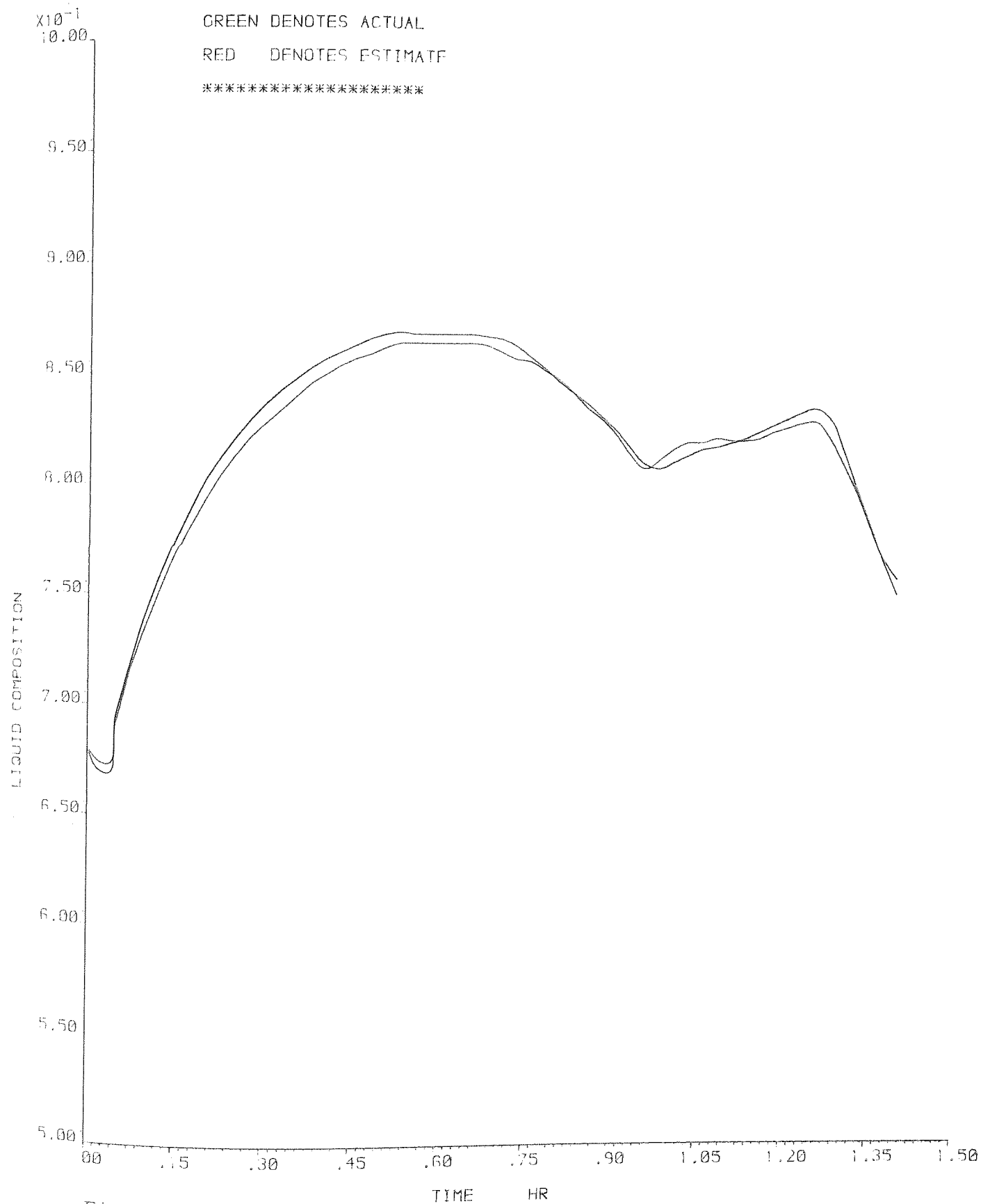


Figure VII.4  
Simulated and actual liquid compositions on a tray in the  
enriching section



PLATE NUMBER= 7.0

GREEN DENOTES ACTUAL

RED DENOTES ESTIMATE

\*\*\*\*\*

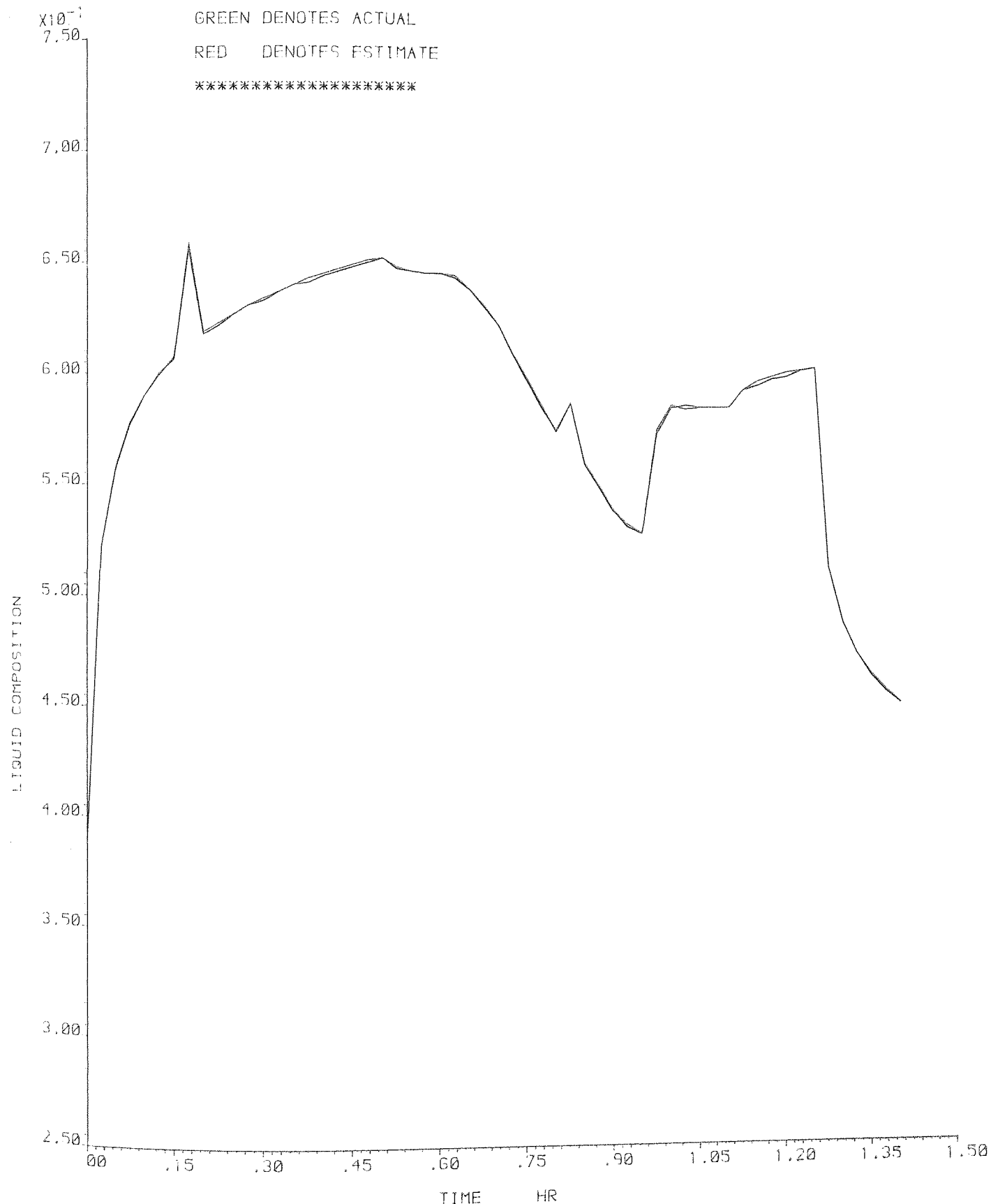


Figure VII.5  
Simulated actual and estimated liquid compositions on the  
feed tray where a corrupt temperature measurement is taken

PLATE NUMBER= 8.0

GREEN DENOTES ACTUAL

RED DENOTES ESTIMATE

\*\*\*\*\*

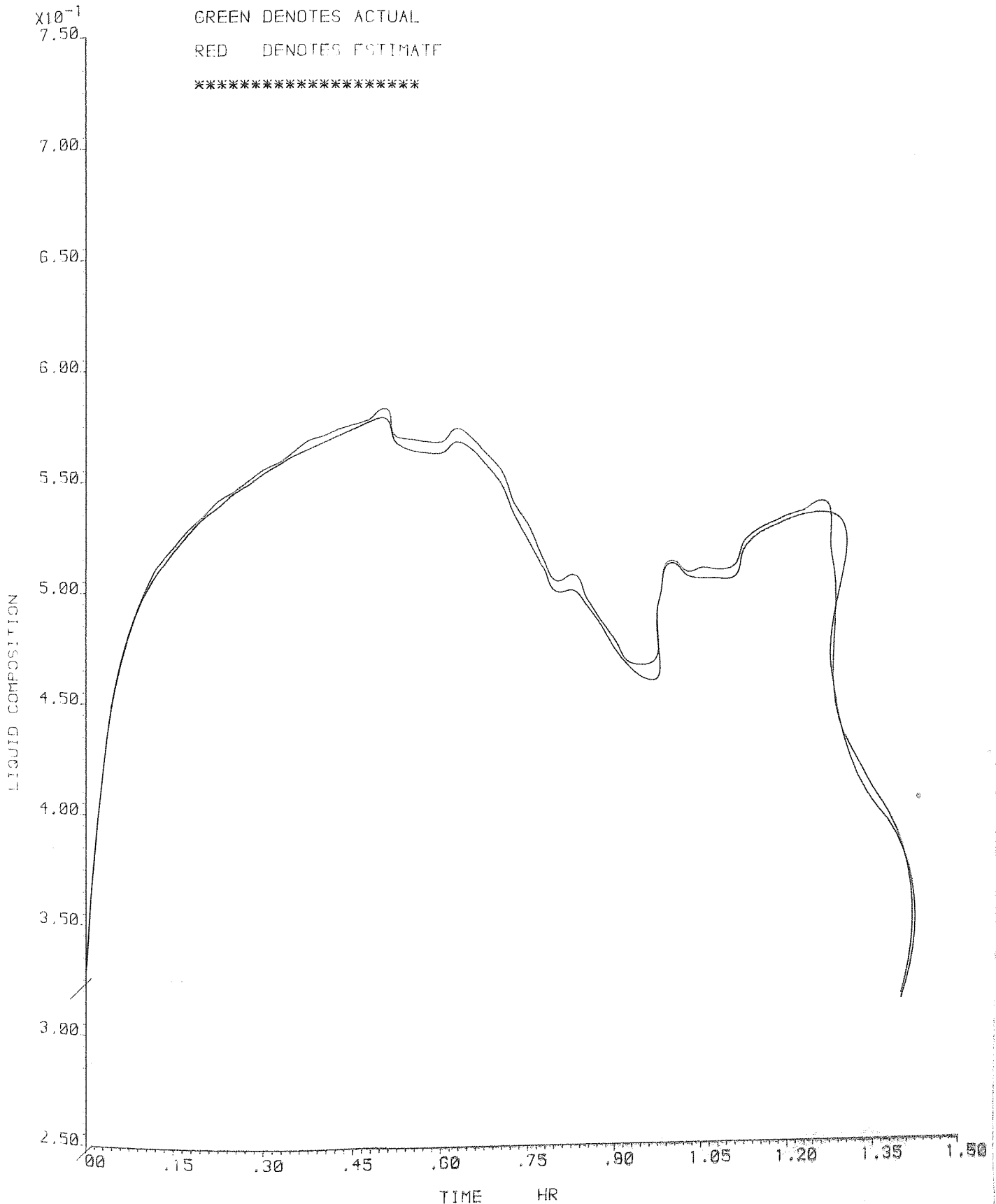


Figure VII.6  
Simulated actual and estimated liquid compositions on a  
tray in the stripping section

PLATE NUMBER= 11.0

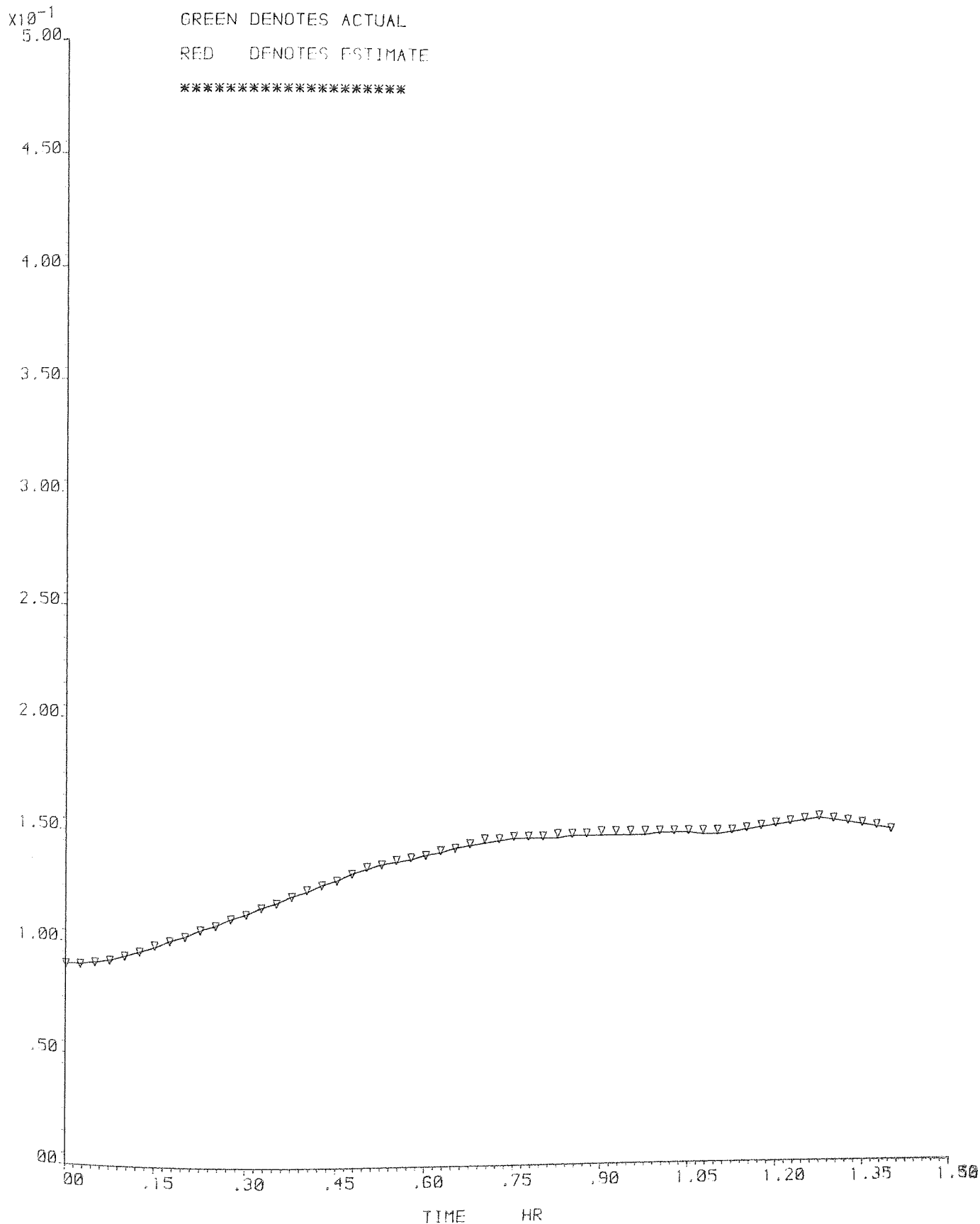


Figure VII.7  
Simulated actual and estimated bottom product compositions

Figure VII.8  
 Simulated multiple step changes in feed rate which is  
 supplied to the filter as a noisy measurement and the  
 estimate produced by the filter. An example of the  
 smoothing action of the filter in the face of intense  
 measurement noise

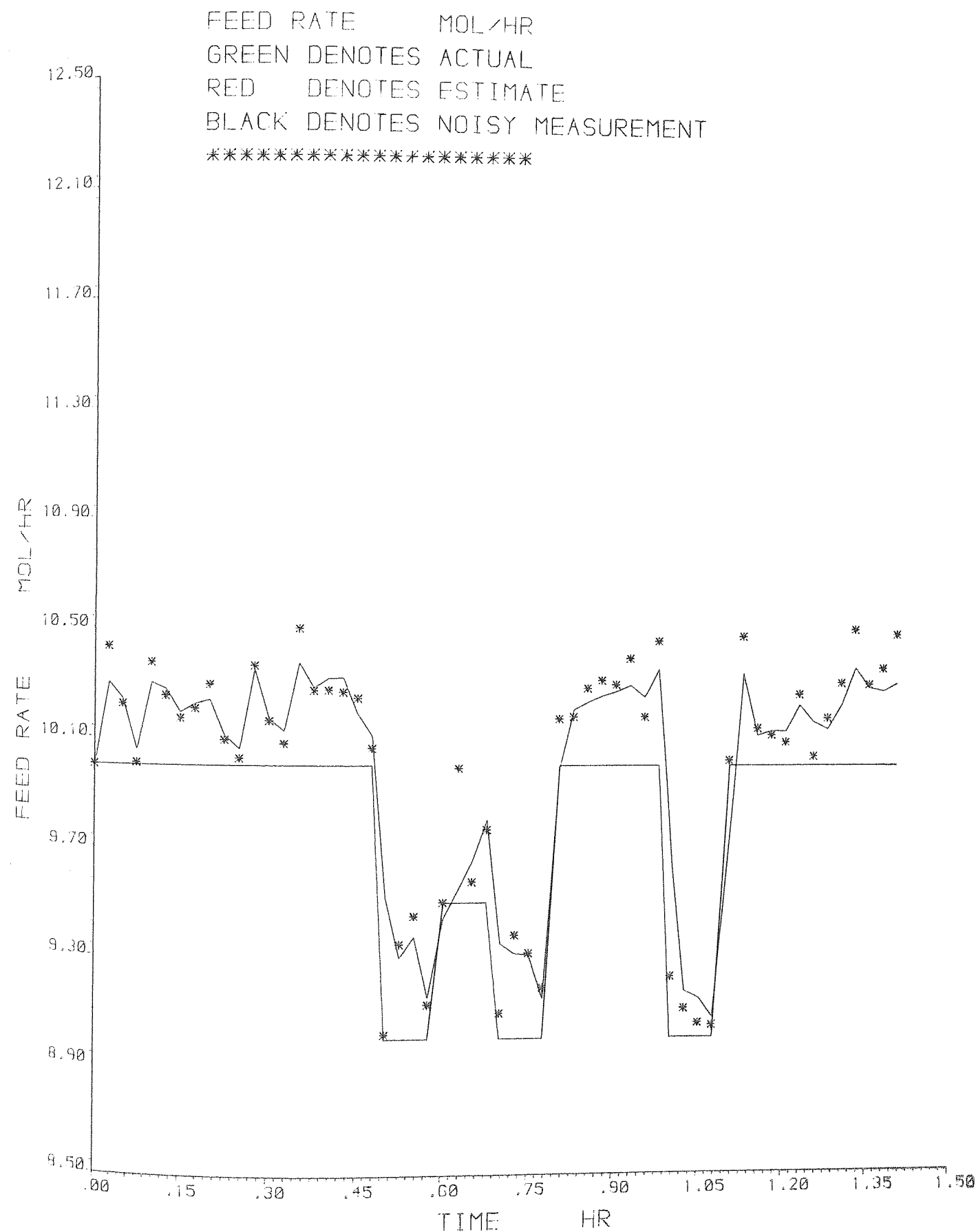


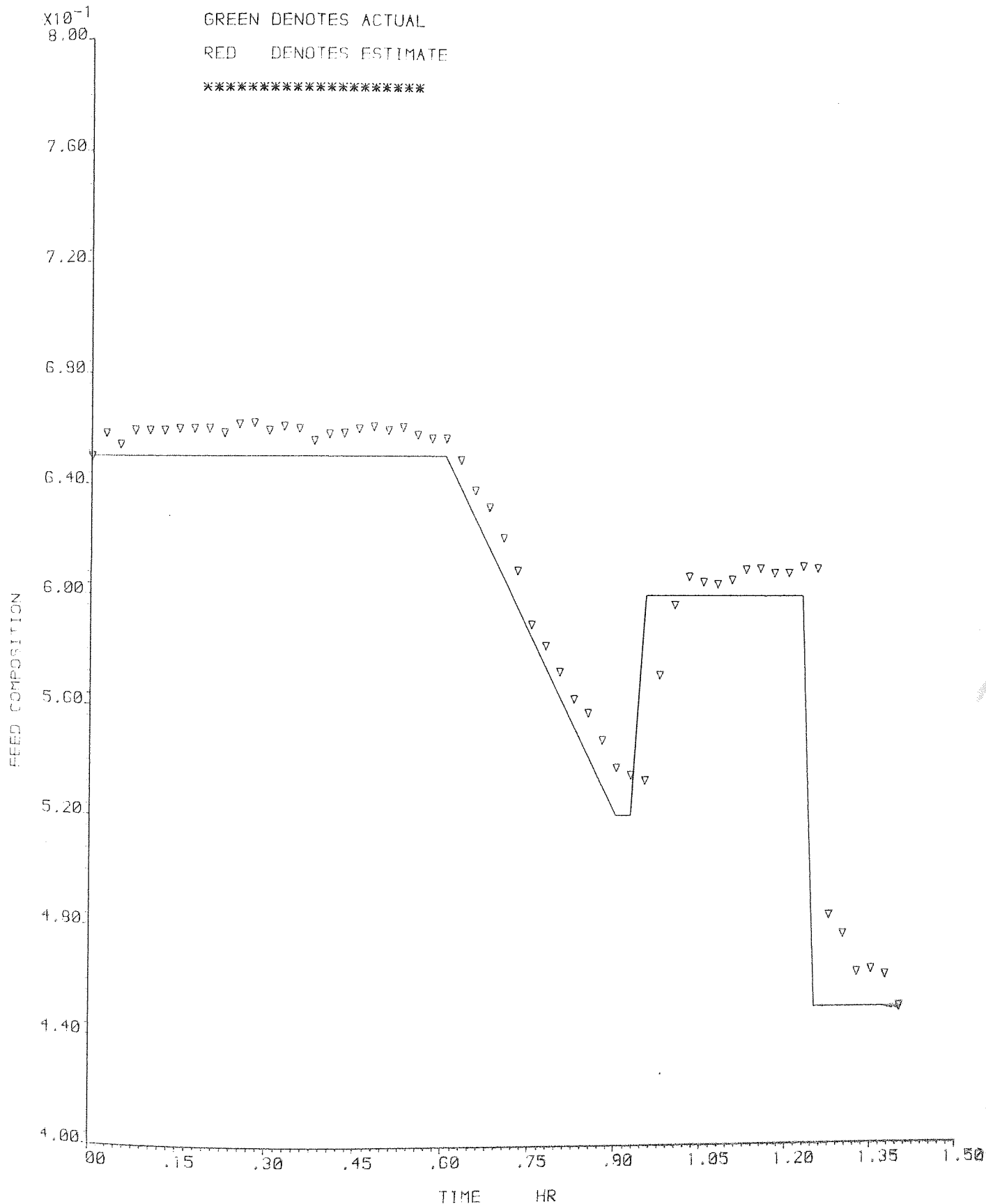
Figure 11-11  
Simulated changes in the feed composition which is  
supplied to the filter as a parameter to be estimated  
and the estimates produced by the filter are compared

FEED COMPOSITION

GREEN DENOTES ACTUAL

RED DENOTES ESTIMATE

\*\*\*\*\*



## VIII.7 DISCUSSION OF THE SIMULATION RESULTS

Generally speaking, it appears that the proposed methodology for the extension of linear filtering theory to nonlinear systems is very effective in that it has almost eliminated the stability problems associated with estimation of a highly nonlinear system with highly nonlinear measurement functional relationships with sample times of up to 40 seconds.

Regarding the tuning of Kalman filters, it appears that this aspect of the design has been rather exaggerated in the past. Although, it may be somewhat lengthy, it certainly is not insurmountable given that the designer approaches the problem with inspired thought and a knowledge of the degree of inaccuracy of the filter's system model and the degree of uncertainty of the measurements. The absolute accuracy of the filter's system model is a secondary consideration. Within reason, no matter how inaccurate the predictions may be, the filter should be able to produce an estimate of the state of the system so long as the inaccuracies are reported to the filter through the  $Q$  matrix. Obviously the quality of the estimate may deteriorate if the filter model is highly inaccurate and in the extreme cases when the model is "too" inaccurate, the estimates may diverge gradually. This is consistent with the notion of seeking an "adequate" filter model (discussed in Chapter VI) that is neither too complex nor too inaccurate but



just delicately balanced. As regards this particular column, the simulation results in Chapter V indicated that the predictions of the filter model (Model I) can differ from the column simulator (Model II) by approximately 10% in terms of composition and in the order of 1% in terms of holdups. These values were good guidelines in starting the tuning procedure. Similar simulation studies can help in any tuning exercise.

With reference to this particular column, the simulation results (Figures VII.3 to VII.9) show that EKF3 is capable of estimating and tracking the tray liquid compositions very accurately from a handful of highly corrupted temperature and flow measurements. The more measurements available, the better the estimates. On this column, the temperature measurements in the stripping section are closer to each other than the enriching section (see Figure VII.2) and therefore the estimates are more accurate in the stripping section.

In Figures VII.3, VII.4 and VII.6 the displayed results are, in actuality, slightly distorted due to the fact that the plotter fits a curve to the points. Had the points been simply joined by straight lines, as in Figure VII.5, the estimates would have been almost indistinguishable from the actual values which is a good reflection of the accuracy of the estimates produced.

In Figure VII.8, the random noise has been added to the measurements as a positive noise which effectively appears as a bias and, if anything, should make life more difficult for the filter. However, this does not seem to trouble it in any way which is further proof for its robustness. Had the noise been added as a zero mean, the estimates would have been more accurate (see Appendix E).

The ability of EKF3 to estimate and track the unmeasured feed composition regardless of sub-cooling of the feed stream (Figure VII.9) should interest control practitioners especially the advocates of feedforward control. The average inaccuracy of the estimates was less 0.5% over 1.5 hours. It also appears that the filter prefers ramp changes to large step ones.

To sum up these results highlight the following powerful features of EKF3:

- (i) its ability to function as a low-cost, fast and accurate on-line analyser with a sample time of only 18 seconds without the associated hardware problems inherent in the operation of on-line analysers. This result is quite encouraging in that it opens tremendous possibilities for overcoming hardware problems by the relatively inexpensive software approach
- (ii) its advantages of accurately estimating the state from secondary measurements as an aid to control

cannot be over emphasized. This will be discussed further in Chapter VIII.

## C H A P T E R   E I G H T

### ESTIMATOR-AIDED FEEDFORWARD COMPUTER CONTROL SIMULATION STUDIES

## VIII.1 INTRODUCTION

In distillation control, it is generally acknowledged that composition control is superior to temperature control. However, on-line measurement of composition is expensive and the measurement lags and sampling delays associated with the measurement are so large as to make it difficult to design even an effective feedback control system. Therefore, the capability of the extended Kalman filter (EKF2 and EKF3) to function as an on-line analyser has already made it a potentially attractive aid to control considering that there are no appreciable time lags in the estimation of tray compositions. Hence, having come thus far, even with feedback composition controllers which use the estimated compositions as inputs, better control must already be within reach.

Feedback controllers, even when designed by the superior multivariable design methods, have not really proven themselves capable of providing optimum control for the slow-moving chemical engineering systems that are subject to unknown disturbances and one cannot help wondering if they ever will. The problems inherent in the stability aspects of these controllers make them even less attractive. Therefore, in this research it is chosen to move away from the feedback control philosophy as far as possible.

## VIII.2 ESTIMATOR-AIDED FEEDFORWARD CONTROL

Since the extended Kalman filter (EKF3) is capable of estimating the known and unknown input disturbances as they enter the system (e.g. feed rate and composition in binary distillation), it becomes very desirable for integration into a feedforward (predictive) control algorithm as shown in Figure VIII.1. Having refined the state and parameters of the system at time  $t$ , the state can then be integrated forward to the next sample time,  $t+\delta t$ , at computer speed to predict the deviations in the controlled states. The predicted deviations can then be fed into the controller which, in turn, computes the control signals required and outputs them to the plant.

Implicit in this picture, also, is the role of the computer which performs the calculations inherent in estimation and also functions as the data acquisitioner and controller.

It now remains to consider the controller synthesis aspects of this proposal. In a single conventional PI controller, by synthesis it is simply meant that the values of  $K$  and  $\tau_I$  need to be determined. Obviously, for complex multivariable systems, one would resort to the multivariable design methods. The multivariable design methods are almost invariably based on linear control theory and thus require that the nonlinear system model be linearized about a



nominal state. Computers can now enable us to consider piecewise linearization and thus synthesis at every sample time to provide better and more stable control. This means that one is effectively proposing a totally adaptive feedforward control structure in which the system model and its controllers can be adapted to the system as time proceeds.

### VIII.3 THE CONSTRAINTS IMPOSED BY THE INTERSAMPLE CALCULATION LOAD

The major ostensible drawback of this proposal may stem from the fact that in on-line real time applications, a considerable amount of calculations may have to be performed during the sample time - especially in high dimensionality systems. In order to construct a stable extended Kalman filter the sample time must be less than one minute in highly nonlinear systems with highly nonlinear functional measurement relationships. This, at first sight, may appear to be a daunting prospect. But it need not be. The truth is that microprocessors (141) have already offered a plausible solution to this problem. If the intersample computation load is excessive, it can be delegated to a number of microprocessors which are supervised by a minicomputer. This means that one is speaking of a parallel-processor arrangement in which the independent parts of the intersample calculations take place simultaneously to save time.

Although microprocessors can help alleviate this problem, an excessive amount of intersample calculation is never desirable. Thus attempts must be made to reduce it where and whenever possible. As regards the construction of the estimator, the model reduction aspects of the design become even more important. An adequate low order filter model, can greatly cut the calculations involved in the estimation part of

this control method. Also, redesigning the controllers at every sample may not be totally justifiable. It may be that controller parameters are best treated as pseudo state variables and estimated stochastically. Such considerations must never be foregone.

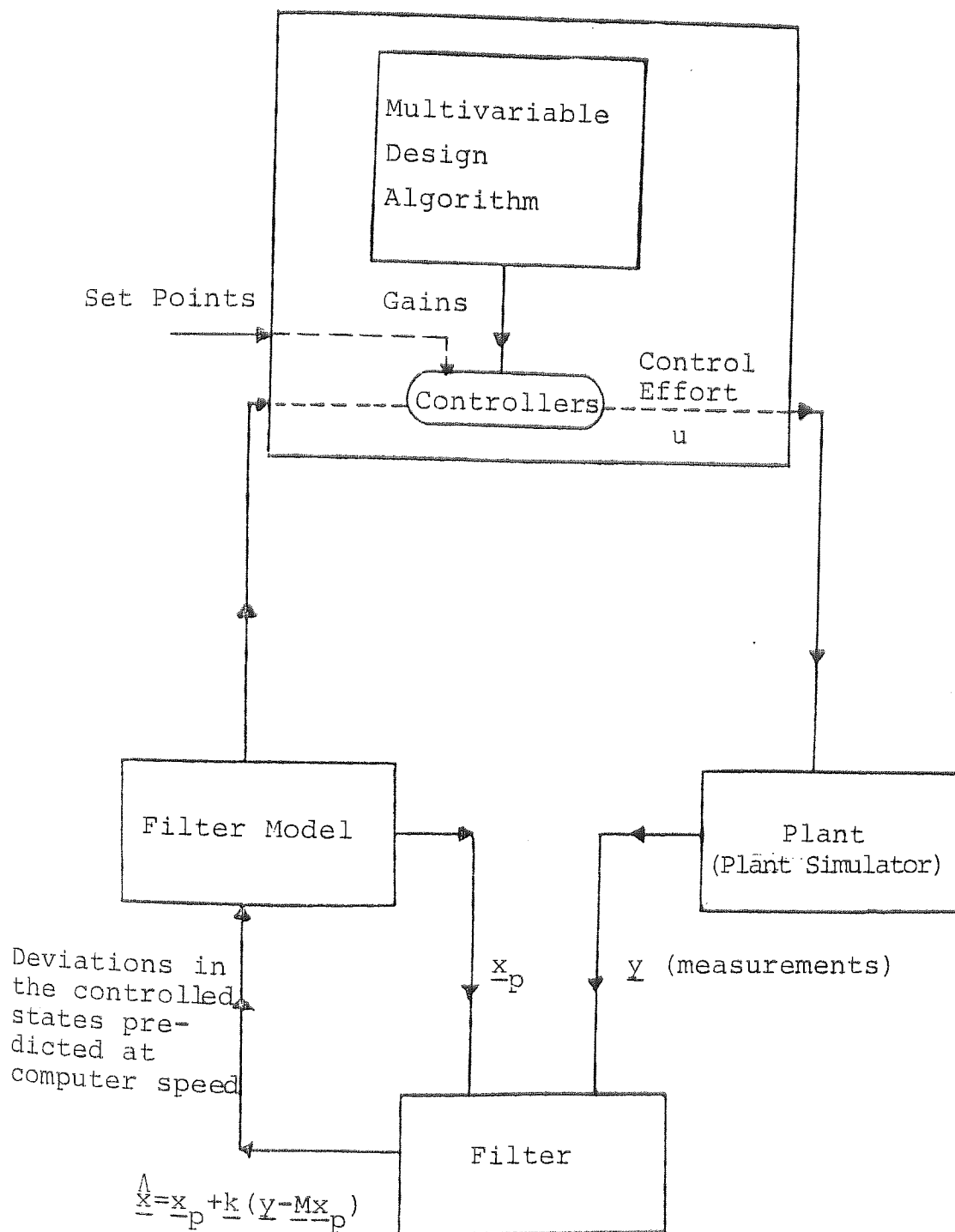


FIGURE VIII.1 - Implementation of Estimator-Aided Feedforward Computer Control

#### VIII.4 THE CHOICE OF MEASURED AND MANIPULATED VARIABLES

So far, the discussion has presupposed an available control configuration in that we have assumed that the measured and manipulated variables (or control inputs) have already been selected and interconnected. A control configuration is normally characterised by:

- (i) a set of variables which are to be controlled to achieve a specified objective
- (ii) a set of variables which are to be measured for control purposes
- (iii) a set of manipulated variables
- (iv) a certain structure for interconnecting the measured and manipulated variables

The first class of control objectives (e.g. product quality control) dictates directly the measurements which should be made for monitoring the process. These primary theoretically desirable measurements are not always available. Often they have to be substituted by secondary ones. This is where the filter plays an important role. The choice and number of secondary measurements and their associated estimation problems can be examined independently of other decisions. The following factors can affect the choice and the number of the secondary measurements:

- (i) economic factors
- (ii) engineering judgement
- (iii) theoretical considerations such as observability criterion for the estimator

Selection of the manipulated variables will affect the response capability to external disturbances and the ability to keep the controlled states at their desired values continually. The more manipulated variables available, the better will be the control of the process. Almost invariably, structural aspects of the processing systems and the physicochemical equations describing the processing unit are the dominant factors in establishing feasible sets of manipulated variables. Govind and Powers (141) have listed a number of qualitative conditions that the selected manipulated variables should satisfy. Among these are reliability, ease of operation, startup and shutdown, and to avoid the manipulation of variables which influence a large number of other variables.

It now remains to consider the interconnection of the measured and manipulated variables. Solution to this will again be guided partly by engineering judgement and partly by theoretical considerations. Engineering judgement usually draws on the past experience and is more relevant to simple systems while methods such as degrees of freedom studies or modal analysis can provide a powerful basis for the theoretical approach for complex processes such as



distillation.

The final stage of the exercise is the synthesis of the controllers. It is almost universally recommended that multivariable design methods should be used for multivariable processes. Such methods include:

- (i) multivariable feedforward
- (ii) optimal feedforward

## VIII.5 THE MAIN FEATURE OF ESTIMATOR-AIDED FEEDFORWARD (EAFF) CONTROL

For convenience of notation, estimator-aided feedforward control will henceforth be abbreviated to EAFF control. EAFF control is essentially characterised by:

- (i) its feedforward philosophy which largely minimises the undesirable effect of time lags on the system's response. Also, EAFF controllers do not appear to suffer from the stability problems which can arise during the simultaneous operation of feedback controllers
- (ii) a number of controllers preferably designed by the multivariable design methods
- (iii) nonlinear dynamics and linear or piecewise linear control
- (iv) feedback information through the estimator which promotes self-correction
- (v) its adaptive nature in that the model can be made to track the system, its parameters, and its controller parameters

## VIII.6 APPLICATION OF EAF CONTROL TO BINARY

### DISTILLATION

The distillation column discussed in Chapter III is used as an example. The binary liquid system is trichloroethylene (MVC) and tetrachloroethylene mixture with the composition of MVC in the feed equal to 0.65.

#### VIII.6.1 THE CONTROL OBJECTIVE

The objective is to control the liquid compositions on trays 1 and 10 at their desired setpoints regardless of the known and unknown disturbances introduced randomly or deterministically.

#### VIII.6.2 THE MANIPULATED VARIABLES

The possible manipulated variables are:

- (i) the distillate offtake rate
- (ii) the bottoms offtake rate
- (iii) the heat input rate
- (iv) the reflux rate

Of these the distillate and bottoms offtake rates are needed to control the reboiler and reflux drum holdups to get the column to operate under steady-state conditions. Therefore, the heat input and reflux rates are available for composition control.

The counterpart of this configuration in the feed-back temperature-control sense is to use the temperature on tray 1 to control the reflux rate and the temperature on tray 10 to control the heat input rate (Figure VIII.2). The performance of EAFF control will be compared with this control structure quantitatively. The performance index will be the familiar Integrated Absolute Error (IAE) criterion:

$$IAE = \int_{T_1}^{T_2} \{ |(x_1 - x_{1,s})| + |(x_{10} - x_{10,s})| \} dt$$

where

$x_j$  and  $x_{j,s}$  are the liquid composition on the  $j$ th tray and its desired setpoint

and here  $T_2$  is chosen to be  $T_1 + 55$  minutes

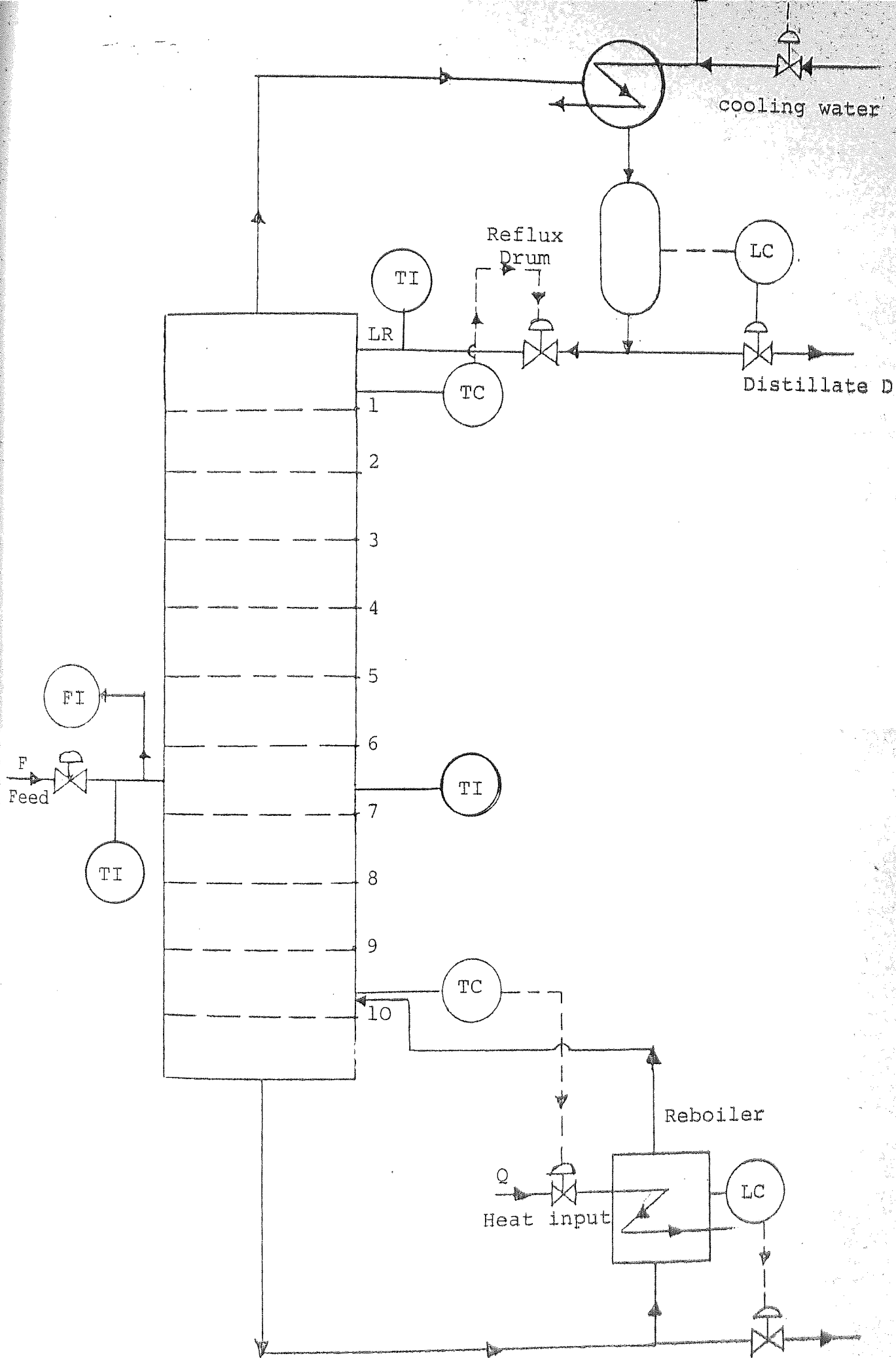


FIGURE VIII.2 - The Feedback Temperature Control Scheme used for Comparison with EAFV Control. Bottoms,  $L_0$

## VIII.7 CONTROLLER DESIGN

### VIII.7.1 EAFF SCHEME

As the starting point two PI controllers are used in the EAFF control scheme. These controllers were designed individually by the reaction curve method (1) on the column simulator. They were then detuned to allow for interaction when operating simultaneously.

The method of implementation of these controllers on a digital computer is discussed by Daie (134). The controller equations are

$$LR = LR_s - 100.0(e_{t,i} + \frac{1}{0.009} \sum_{i=1}^n e_{bi})$$

$$Q = Q_s + 800.0(e_{b,i} + \frac{1}{0.0018} \sum_{i=1}^n e_{b,i})$$

where

$$e_t = x_1 - x_{1,s}$$

$$e_b = x_{10} - x_{10,s}$$

LR = reflux rate            mol./hr.

Q = heat input            kJ./hr.

LR<sub>s</sub> and Q<sub>s</sub> the steady-state biases for R and Q  
respectively

x<sub>i,s</sub> are the setpoints



### VIII.7.2 FEEDBACK TEMPERATURE CONTROL SCHEME

The two PI temperature controllers used were also designed using the reaction curve method and detuning on the column simulator. The controller equations are:

$$LR = LR_s + 150(e_{t,i} + \frac{1}{0.015} \sum_{i=1}^n e_{t,i})$$

$$Q = Q_s - 30.(e_{b,i} + \frac{1}{0.0027} \sum_{i=1}^n e_{b,i})$$

where

$$e_{t,i} = T_1 - T_{1,s}$$

$$e_{b,i} = T_{10} - T_{10,s}$$

and  $T_{i,s}$  are the temperature setpoints

### VIII.8 EAFF CONTROL SIMULATION PACKAGE : THE MAIN PROGRAM SEGMENTS

The main program segments for EAFF control simulation are essentially the same as those in the estimation package except that two more subroutines are added. These are:

SUBROUTINE CONSET - Subroutine to define the controller settings

SUBROUTINE CONTR2 - Subroutine to implement two PI controllers

The main program arrangement is shown in Figure VIII.3. The full documentation of this package is given in Appendix F (Microfiche).

### VIII.9 FEEDBACK TEMPERATURE CONTROL SIMULATION PACKAGE

This package is obtained simply by inserting a subroutine in the process simulator to implement two PI feedback temperature controllers. The main program arrangement is depicted in Figure VIII.4.

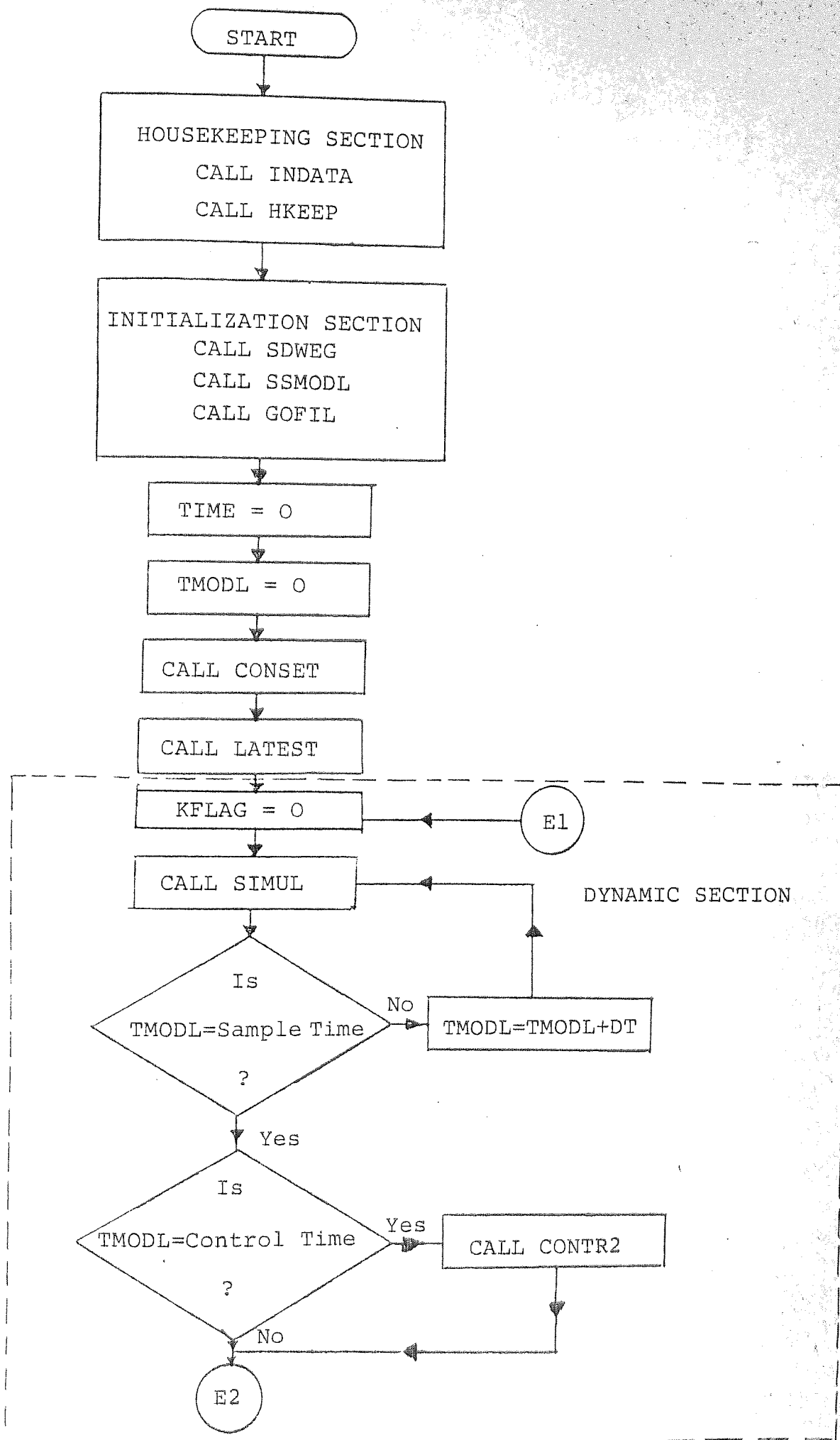


FIGURE VIII.3 - The Main Program Arrangement for EAPF Control Package

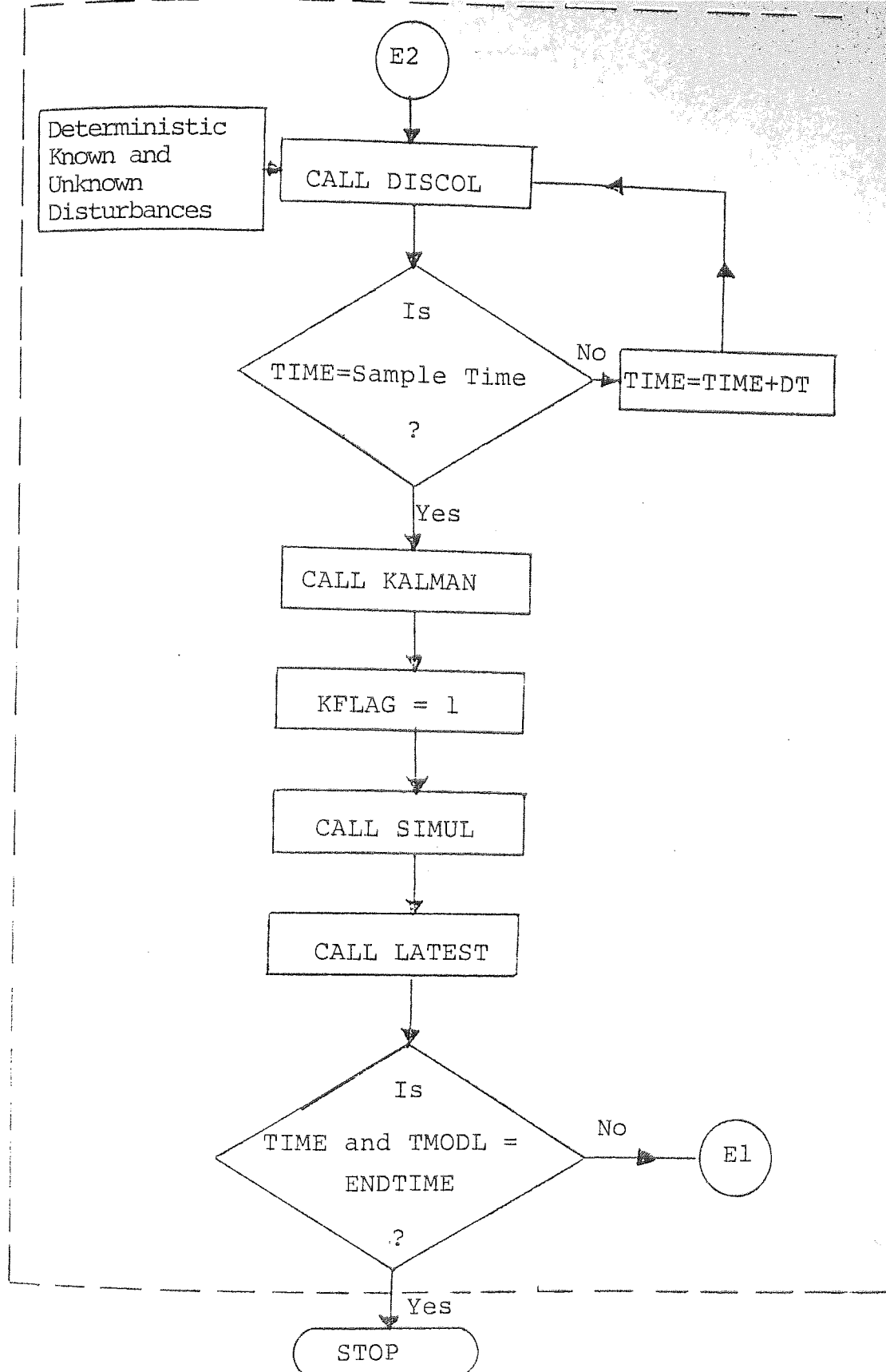


Figure VIII.3 Continued

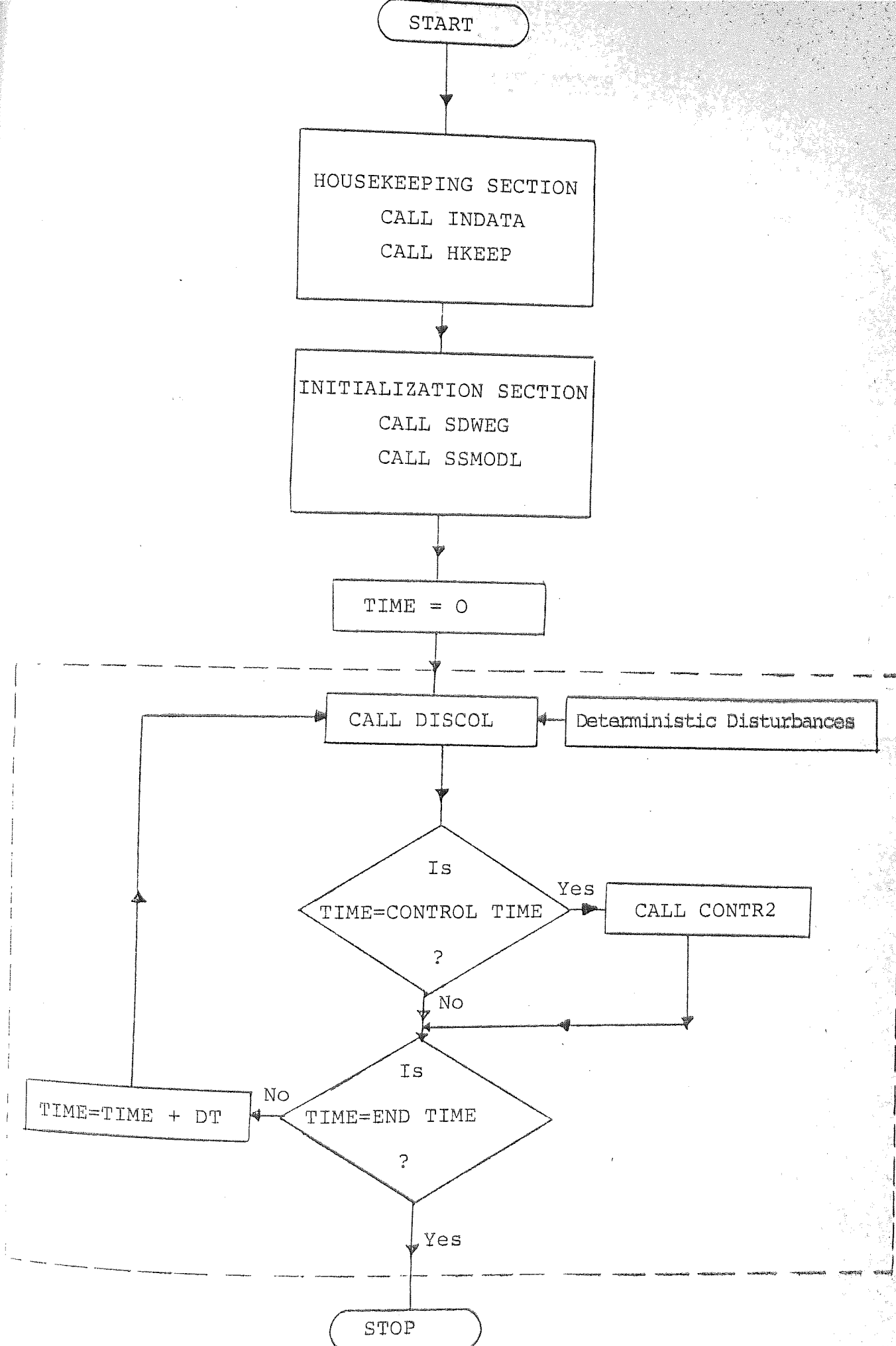


FIGURE VIII.4 - The Main Program Arrangement for the Implementation of Feedback Temperature Control.

## VIII.10 CONTROL SIMULATION EXPERIMENTS

The following experiments were carried out to assess and demonstrate the advantages offered by EAFF control and its promising features:

- (i) the response of the column to a 10% sustained step increase in the feed rate under EAFF control compared with its response under feedback temperature control. The responses are compared graphically (Figures VIII.5 and VIII.6) and quantitatively via their respective IAE's. The sample time was chosen to be 18 seconds. The IAE's were found to be

EAFF control	:	IAE $\approx$ 0.004 over 55 minutes
feedback temperature control	:	IAE $\approx$ 0.008 over 55 minutes

- (ii) introducing multiple disturbances in the feed rate, composition and temperature and comparing the responses of the column under the two control schemes, i.e. EAFF control and feedback temperature control (see Figures VIII.9 and VIII.10). The sample time was 18 seconds
- (iii) increasing the sample time to 25 seconds with the same multiple disturbances as in experiment 2. The EAFF controllers were still stable and no further tuning was necessary. However, as expected, the overall performance did suffer slightly compared with the case with a sample



time of 18 seconds. This result is produced  
digitally in Appendix F (Microfiche)

- (iv) The sample time was reduced to 10 seconds with  
the same disturbance as in experiments 2 and 3.  
EAFF control produced almost perfect results  
in that the transients in the controlled  
variables were hardly conspicuous

# VIII.11 REMARKS ON THE DISPLAYED CONTROL SIMULATION

## RESULTS

Figures VIII.5 and VIII.6

The responses of the column to a 10% sustained step increase in the feed rate under EAFF and feedback temperature controllers are compared. The sampling interval for the EAFF control was chosen to be 18 seconds - well within the dominant time constant of the system. It can be seen that the controlled variables undergo less transients under EAFF control and take less time to return to their respective setpoints. The feedback temperature controllers are very tightly tuned and, therefore, the computed IAE of 0.008 associated with them is very conservative. In real-life one would not risk tuning the controllers so tightly and thus the IAE would be greater than 0.008 which is further proof for the superiority of EAFF control whose IAE was approximately 0.004 over the same time interval. It is also worth noting that these results are obtained on a column with a reboiler whose manipulated variable contains minimal time lag. On a larger column and in the face of a time lag in the manipulated variable's response, the performance of the feedback controllers would be expected to deteriorate markedly whereas the EAFF controllers should not be troubled by these

problems by the virtue of their feedforward philosophy.

#### Figures VIII.7 and VIII.8

These graphs highlight the second interesting difference between the feedback temperature and EAFF controllers. It can be seen that EAFF controllers find the new values for the manipulated variables for the new steady-state more rapidly. Naturally, this is an additional advantage in that it means much less off-specification tray compositions are produced in the face of a sustained step increase in the feed rate.

#### Figures VIII.9 and VIII.10

The response of the column to multiple disturbances in the feed rate, composition and temperature under EAFF and feedback temperature controllers are compared. It can be seen that regardless of the type and time of the disturbances the EAFF controllers restore the controlled variables to their setpoints efficiently. Although, under feedback temperature controllers, the controlled variables appear to tend towards their setpoints initially, as further disturbances are introduced they become oscillatory indicating that the column is tending towards instability. This is a good example of the

robustness of the EAFF controllers in that they continue to perform well without any need for further tuning.

Figures VIII.11 and VIII.12

Another demonstration of the orderly manner in which the control inputs are manipulated to restore the controlled variables to their desired setpoints by EAFF controllers. Notice that in Figure VIII.11, the boilup rate is plotted against time instead of the actual heat input rate,  $Q$ . The variations of the boilup rate should portray the variations in  $Q$ . Thus EAFF control appears to be more economical in terms of energy consumption too.

PLATE NUMBER= 1.0  
 GREEN EAFF CONTROL  
 RED FEEDBACK TEMP. CONTROL

\*\*\*\*\*

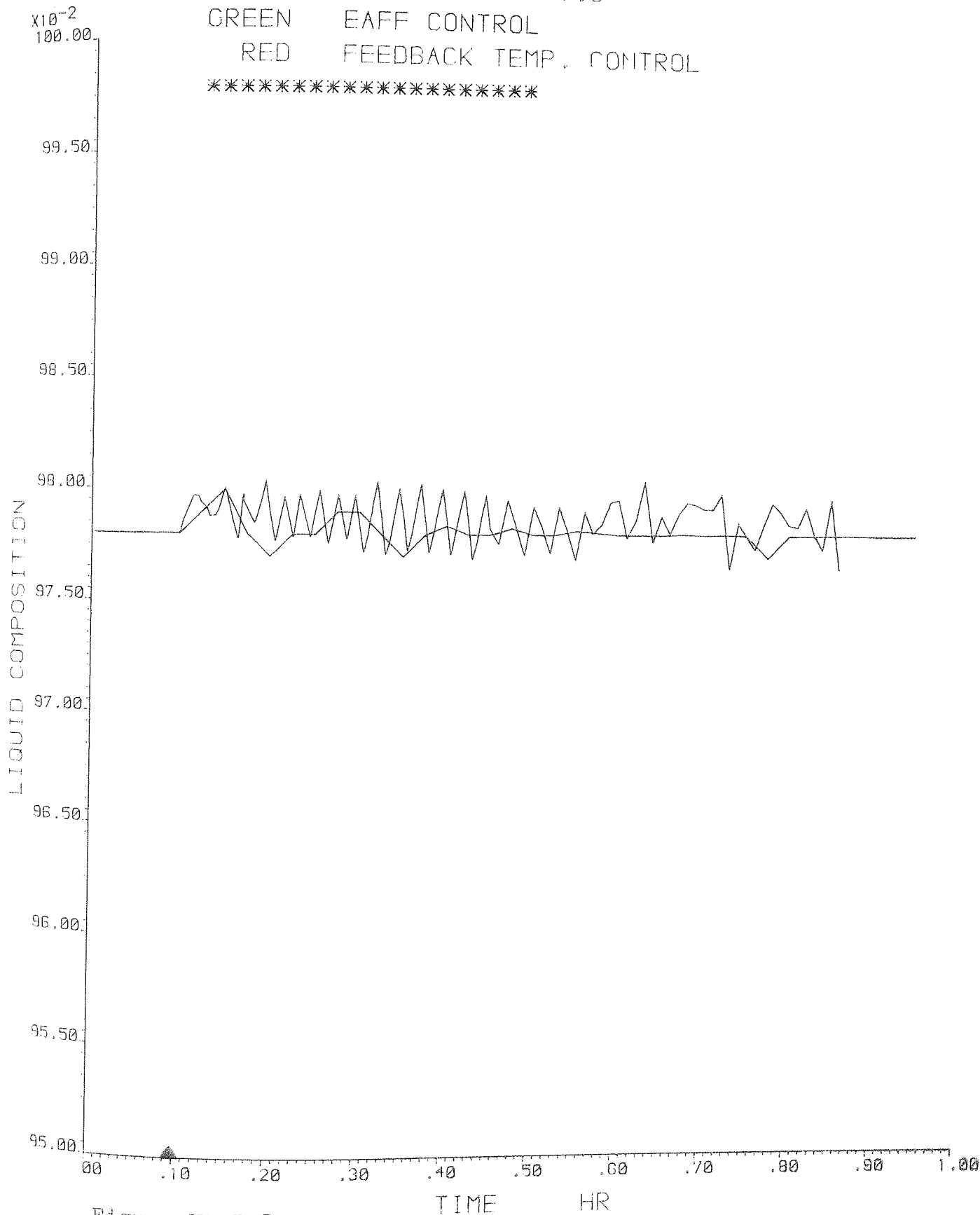


Figure VIII.5

The responses of the column to a 10% step increase in the feed rate under EAFF control and feedback temperature control

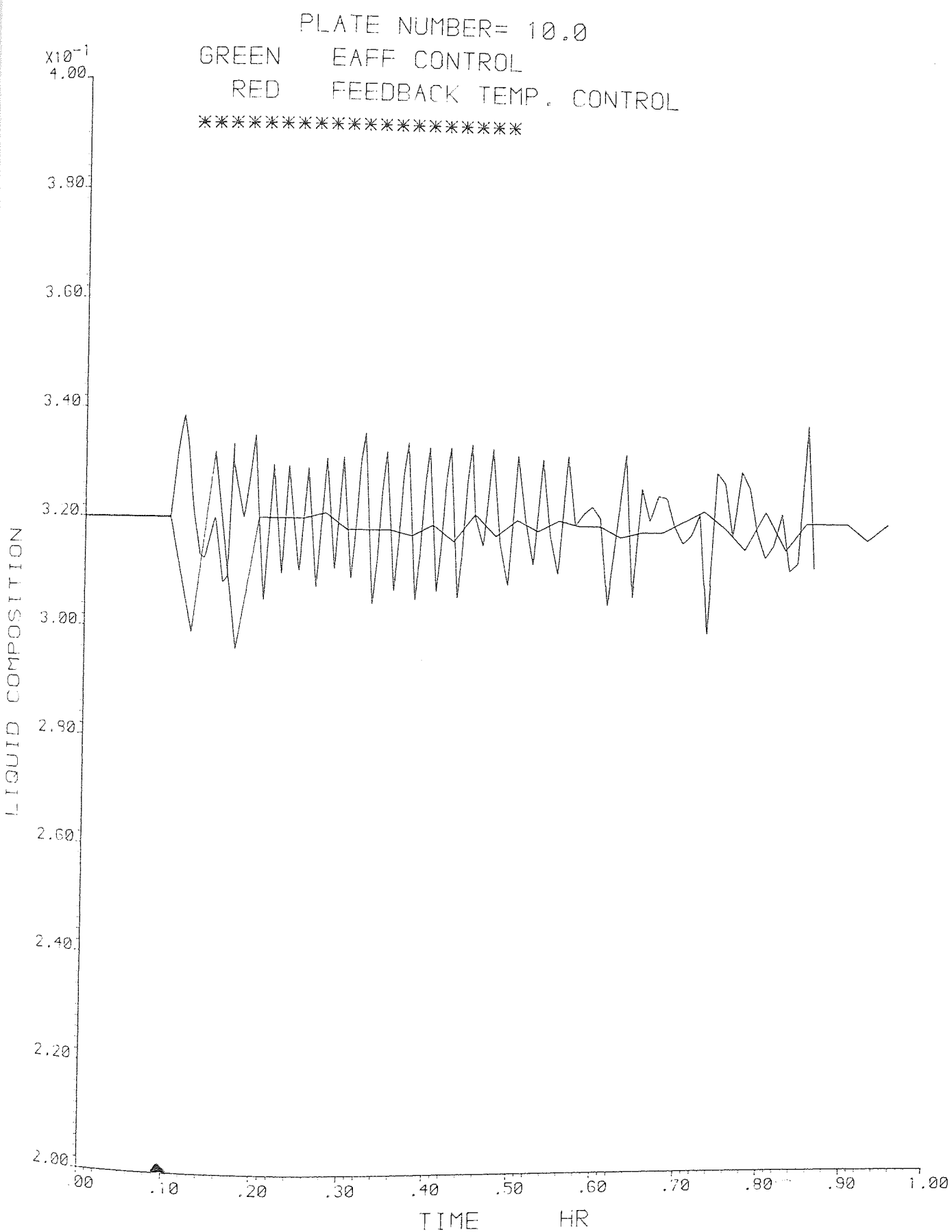
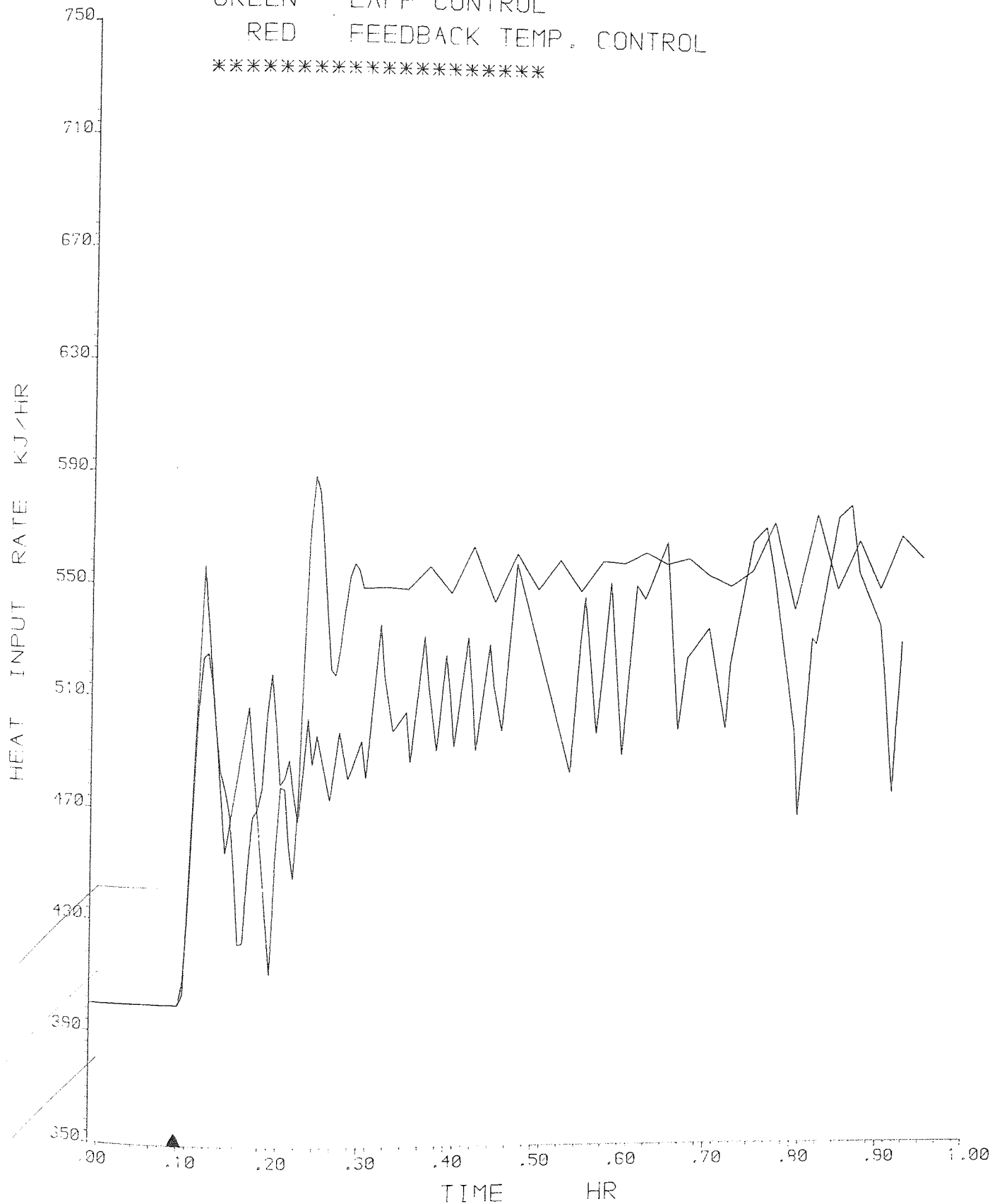


Figure VIII.6  
The responses of the column to a 10% step increase in the  
feed rate under EAFF control and feedback temperature control



Figure VIII.7  
Manipulation of the heat input rate by EAFF controllers  
compared with the manipulation by feedback temperature  
controllers when the column is subjected to a 10% step  
increase in the feed rate

HEAT INPUT RATE KJ/HR  
GREEN EAFF CONTROL  
RED FEEDBACK TEMP. CONTROL  
\*\*\*\*\*



REFLUX RATE MOL/HR  
 GREEN EAFF CONTROL  
 RED FEEDBACK TEMP. CONTROL

\*\*\*\*\*

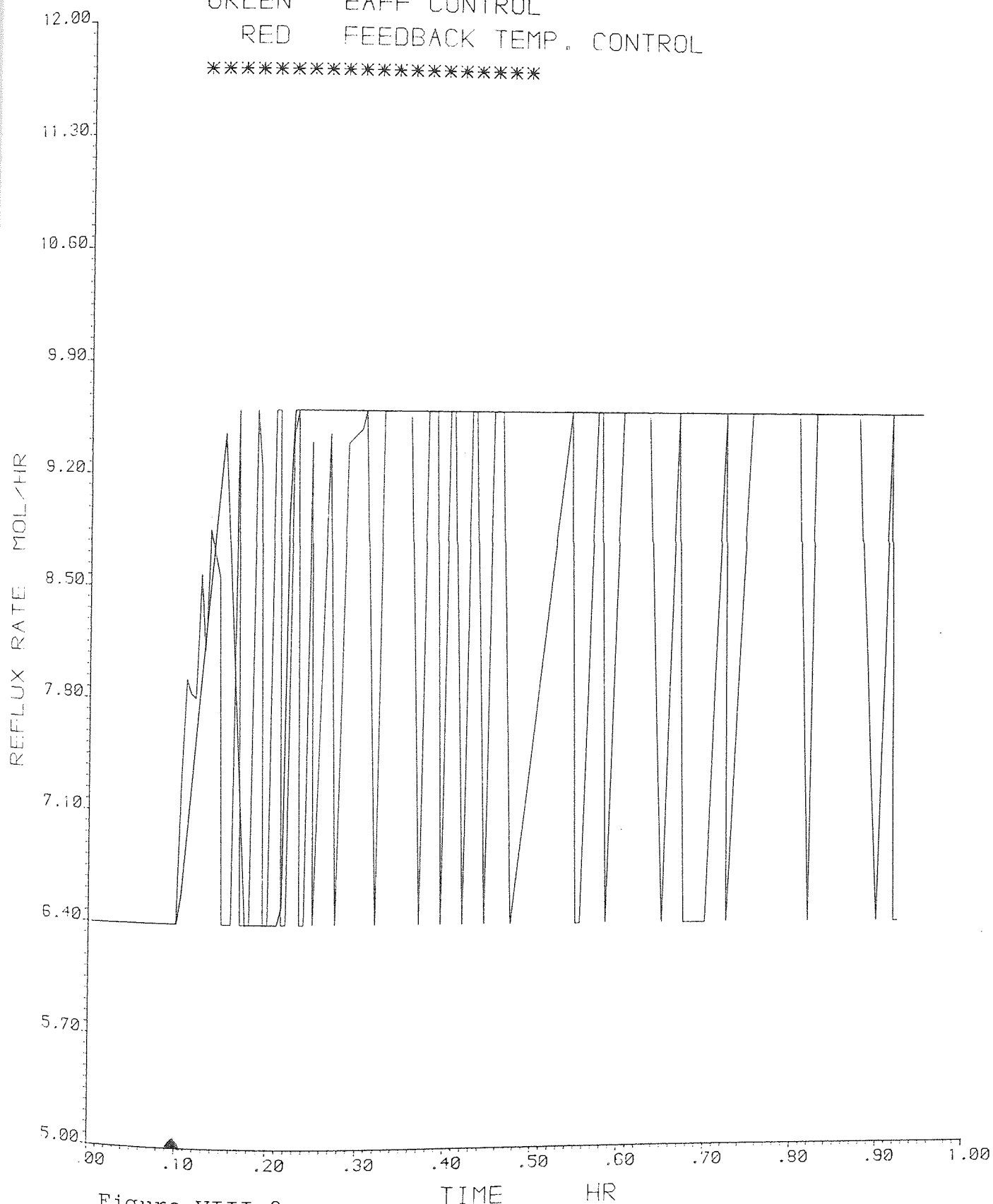


Figure VIII.8  
 Manipulation of the reflux rate by EAFF controllers compared  
 with the manipulation by feedback temperature controllers  
 when the column is subjected to a 10% step increase in the  
 feed rate

Figure VIII.9

The responses of the column to multiple changes in the feed rate, composition and temperature under EAFF control and feedback temperature control

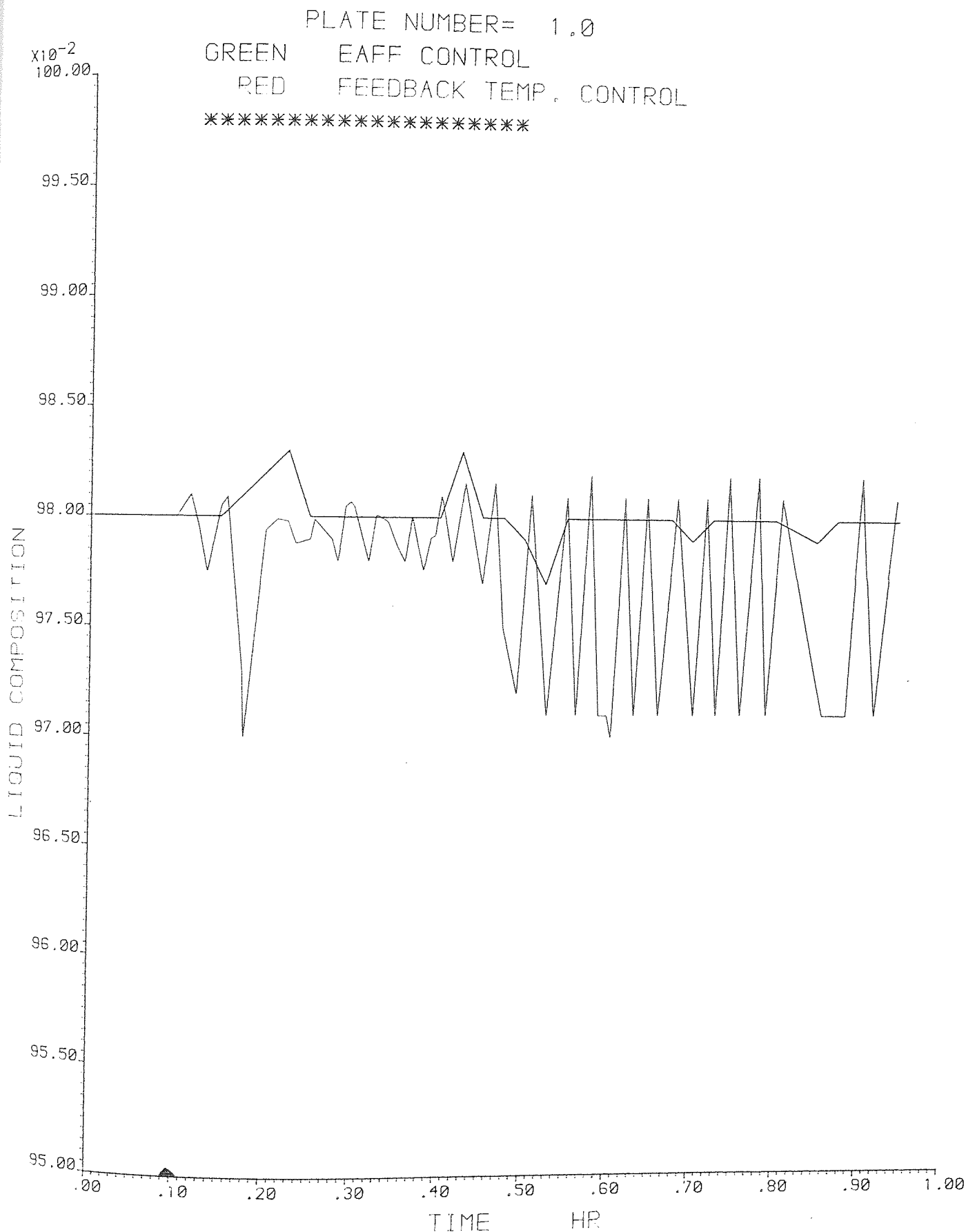


Figure VIII.10

The responses of the column to multiple changes in the feed rate, composition and temperature under EAFF control and feedback temperature control

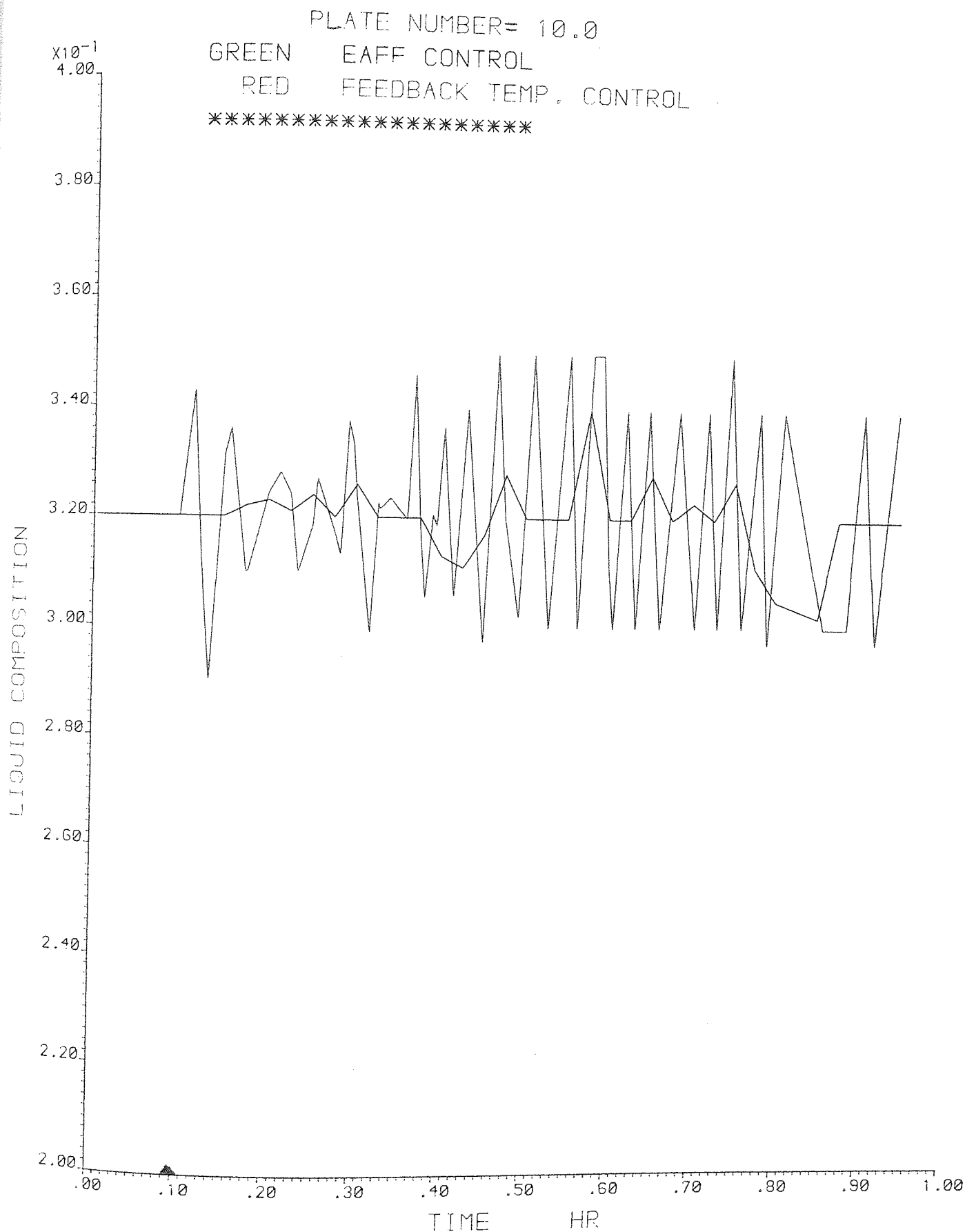


Figure VIII.11

Manipulation of the boilup rate by EAFF controllers compared with the manipulation by the feedback temperature controllers when the column is subjected to multiple changes in feed rate, composition and temperature

BOILUP RATE MOL/HR  
GREEN EAFF CONTROL  
RED FEEDBACK TEMP. CONTROL

\*\*\*\*\*

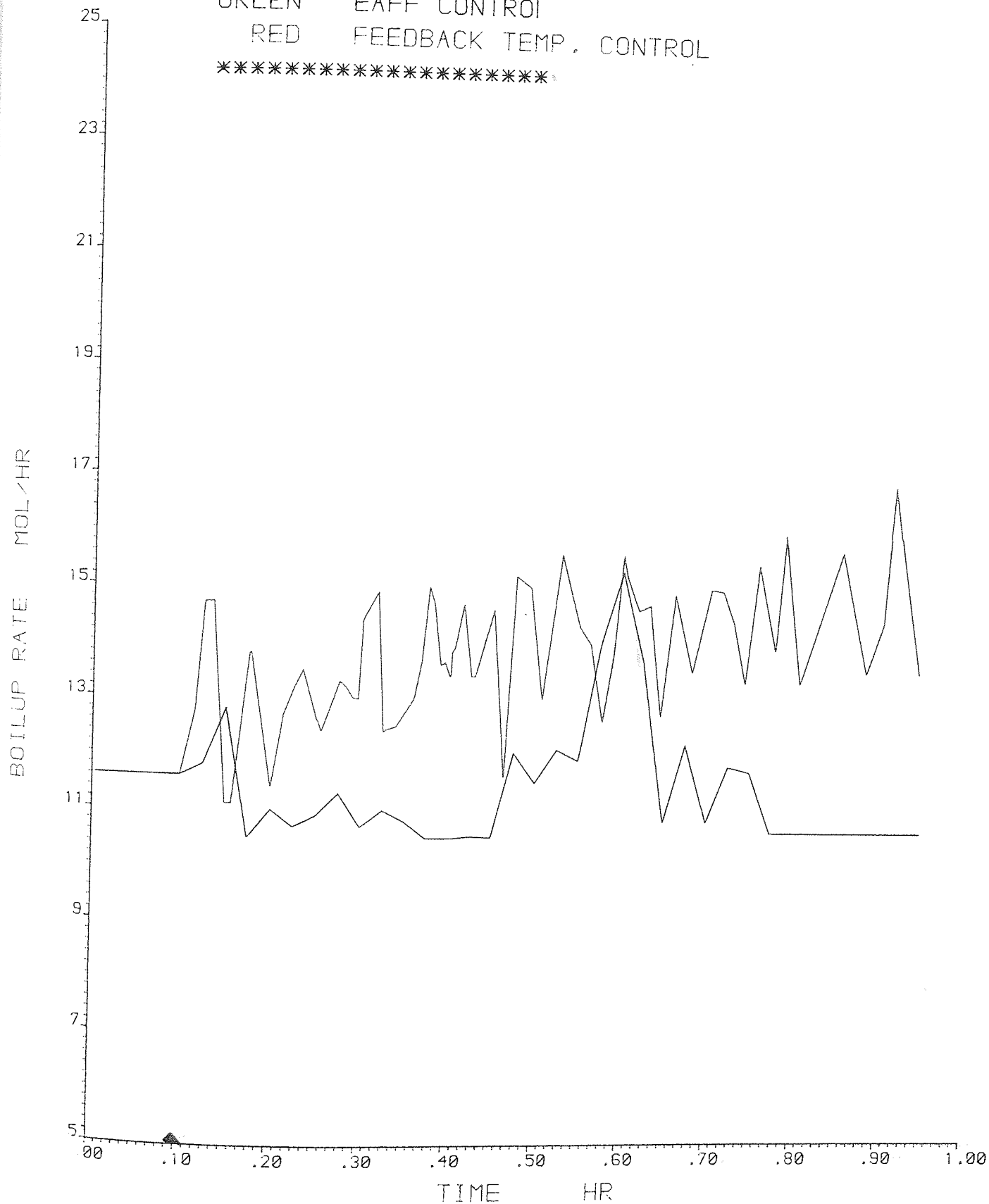
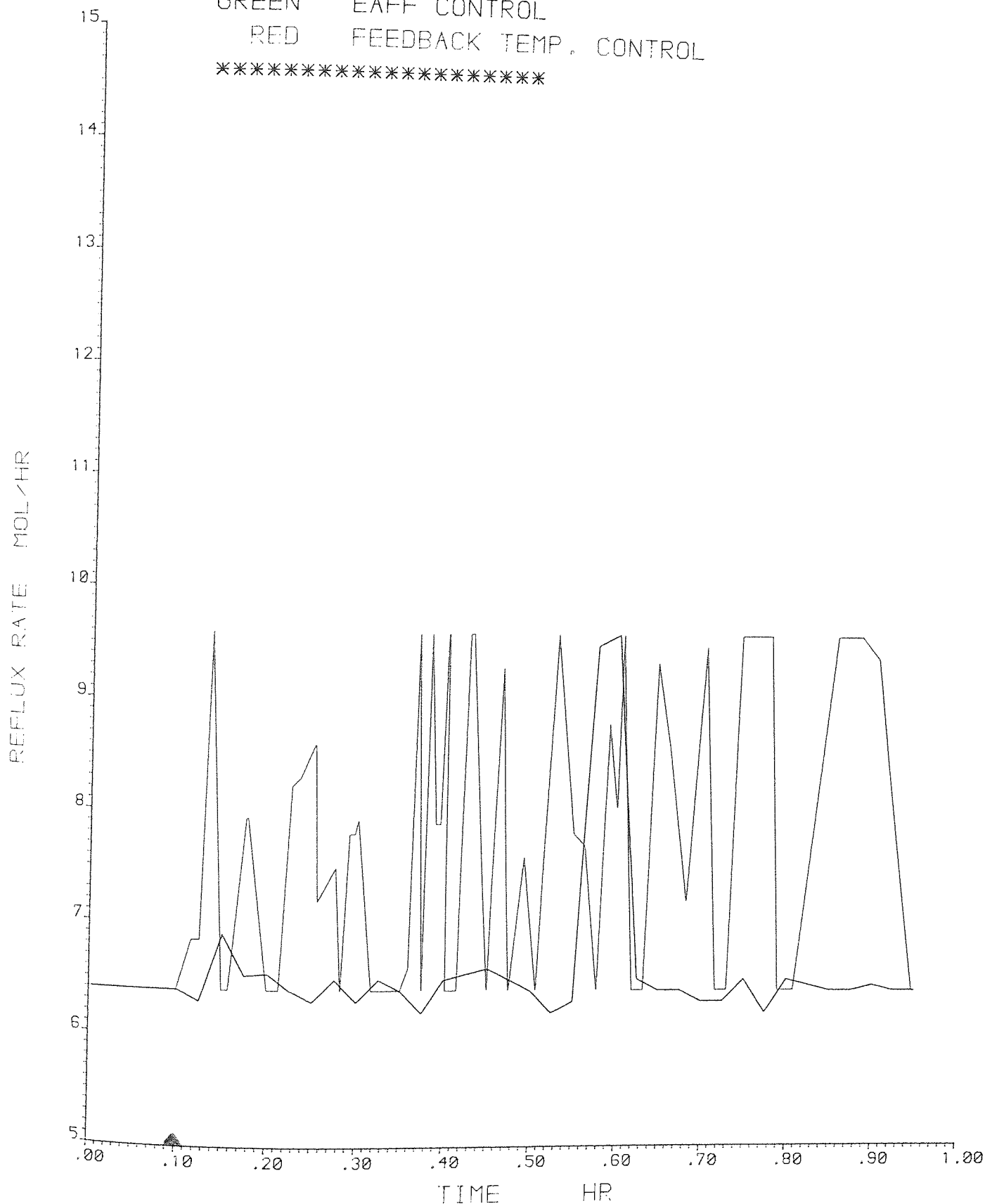


Figure VIII.12

Manipulation of the reflux rate by EAFF controllers compared with the manipulation by feedback temperature controllers when the column is subjected to multiple changes in feed rate, composition and temperature

REFLUX RATE MOL/HR  
GREEN EAFF CONTROL  
RED FEEDBACK TEMP. CONTROL

\*\*\*\*\*



## VIII.12 DISCUSSION OF CONTROL SIMULATION RESULTS

From Figure VIII.5 and VIII.6 it can be seen that EAFF controllers take much less time to settle and bring the compositions to their desired values than the feedback controllers. These graphs also highlight the typical interaction effects that occur during the operation of multiple feedback controllers whereas the EAFF ones do not appear to suffer from these problems.

Even on a column with a reboiler whose manipulated variable contains minimal time lag, the performance of EAFF controllers is still twice as good as the feedback ones in terms of their respective IAE's. One of the main advantages of EAFF control lies in its ability to combat the undesirable effect of time lags on the system's response whereas the performance of feedback control would be expected to deteriorate dramatically in the face of time lags. Therefore, comparatively speaking, in a more realistic situation and on a larger column, EAFF control should be even more effective and robust than feedback.

Another interesting feature of EAFF control is that it appears to be capable of finding the right adjustments to the manipulated variables much more efficiently (see Figure VIII.7 and VIII.8). This is advantageous in terms of the economy of operation in that it means less off specification tray compositions. EAFF control also appears to be more economical in



terms of energy consumptions (see Figures VIII.11). This is the second most attractive feature of EAFF control.

The sampling interval chosen for EAFF control during this experiment was 18 seconds - well within the dominant time constant of the column (20 minutes approximately). In an on-line real-time application another important consideration in choosing the sampling interval would be for it not to be too small so as to commit the control computer to just sampling the process instruments and not having time to perform other tasks.

When multiple disturbances were introduced into the column, the feedback controllers made the system unstable (Figures VIII.9 and VIII.10) which proves that in the previous experiment these controllers must have been very tightly tuned. Since in real-life one would not run the risk of tuning the controllers so tightly the computed IAE used for comparison with EAFF control is very conservative and this provides further proof for the superiority of EAFF controllers.

When the sample time was increased to 25 seconds, the EAFF controllers did suffer slightly and took a little longer to bring the controlled variables back to their desired values. This is because the same predictions of the state are used for estimation and for control. The bigger the sample time, the less accurate the predictions and the less accurate the

control. If, however, having computed the predicted state for control the filter model is reintegrated with the new values of the manipulated variables for estimation, the estimation and control should improve.

C H A P T E R   N I N E

DISCUSSION AND RECOMMENDATIONS FOR FURTHER WORK

## IX.1 DISCUSSION

The discussion of this research will include:

- (i) the construction and instrumentation of the column
- (ii) dynamic simulation
- (iii) estimation
- (iv) control

## IX.2 THE CONSTRUCTION OF THE COLUMN

The original design and the present construction of the column deserve some discussion with reference to:

- (i) the reboiler
- (ii) the gravity flow arrangement

The reboiler is physically oversized which means that its holdup is disproportionately larger than that of a typical tray - by a factor of ten thousand. This makes the bottom product composition almost insensitive to load variations in the column and, therefore, pointless control. It was also found to be somewhat electrically under-powered as, even at the maximum setting, it just produced enough vapour to run the column at steady state and study its dynamics subject to throughput changes.

Due to financial constraints, the notion of gravity flow had to be employed in the reflux and

distillate lines by adding a pipe section to the top of the column. This arrangement was suspected to be problematical and this suspicion was later confirmed by the amount of trouble experienced during the operation of the column and also during the modelling of the heat losses from it. The main criticisms of this arrangement are:

- (i) it makes the off-line modelling very difficult and the on-line modelling virtually impossible
- (ii) it complicates the flow measurements unduly
- (iii) it creates extra unwanted heat load for the reboiler

The problem of extra heat load on the already under-powered reboiler effectively hampered control experiments even with simple feedback temperature controllers.

For on-line estimation and control experiments the following modifications to the column are thought to be imperative:

- (i) the notion of gravity flow must be abandoned and the associated pipe section should be removed. This will eliminate the extra heat load on the reboiler and may enable it to provide the extra heat needed for control experiments
- (ii) the excessive reboiler holdup swamps the variations in the bottoms composition and thus makes it pointless to control the bottom

composition. A redesign of the reboiler is recommended - preferably one that contains a time lag in its manipulated variable's response in order to make it more comparable with an industrial column

It was decided to use a highly corrosive liquid system to ensure the robustness of the column. However, long-term exposure to the fumes from this liquid system can be hazardous and it is therefore recommended that it should be changed.

#### IX.2.1 THE COLUMN INSTRUMENTATION

The temperature and level measurements on the column are sufficiently accurate. However, the flow measurements need to be improved for on-line estimation and control. At least two accurate flow measurements are needed in the reflux and feed lines for on-line modelling. A more accurate level measurement at the reboiler may also be subservient to on-line modelling.

### IX.3 DYNAMIC SIMULATION

The proposed structure for process simulators (Chapter IV) has proved to be flexible and computationally more efficient than the structures proposed for system simulation. It enables estimation and control routines to be simply inserted into the simulator with ease and little extra programming effort. The extensive simulation work carried out in this research was greatly facilitated by the flexibility of this structure.

As regards dynamic simulation of binary distillation using deterministic models the following points deserve some elaboration:

- (i) the use of the AIChE tray efficiency calculation method
- (ii) the use of Brambilla's equation to incorporate fluid dynamics into the models in the form of tray holdup calculation
- (iii) the assumption of quasi steady state model for vapour rate calculation

The calculation of tray efficiencies by the AIChE method is worthwhile in that it enhances the accuracy of the static and dynamic simulations of distillation. The efficiencies are practically time-invariant during the transient periods for the type of disturbances that are likely to occur. However, during the simulation, they can be recomputed at a predetermined



frequency.

Brambilla's equation for tray holdup appears to be applicable to small diameter columns. In the truncated form of the equation used in this research, the A and B constants were determined from one set of experimental data and checked by subsequent experiments. The typical values provided by Brambilla (110) can serve as starting values during the determination of these constants for a particular type of column.

The stiffness implicit in the distillation models usually forces a small integration step size on their solutions. Hence to avoid excessive running times the policy should be to approximate differential equations by their steady-state counterparts as far as possible if the resulting inaccuracy is tolerable. One of the major problems in the simulation is in the evaluation of the vapour rate. The quasi steady state assumption made to calculate the vapour rate does not appear to be unrealistic for this particular column and perhaps should be considered in every case since it reduces the number of differential equations by a third. An alternative method has also been suggested in Chapter IV which relates the vapour rate to the pressure drop coefficient assuming it to be available. If the pressure drop coefficient is not available, the best method would probably be to integrate the component balance to obtain new values of  $x$  and hence  $y$ ,  $T$  and the liquid and vapour stream

enthalpies. Assuming that the change in the enthalpy is small compared with the heat fluxes, an estimate of the enthalpy derivative ( $dh/dt$ ) may be obtained from the energy balance equation at the latest integration step. The energy balance equation can then be rearranged to obtain the vapour rate on each tray starting from the reboiler.

During the experimental verifications of the column simulation, the predicted tray temperatures differed from the actual ones by  $\pm 0.6$  of a degree centigrade under steady state and transient conditions. This discrepancy is thought to be due to

- (i) the measurement errors : the following measurements are necessary:
  - (a) feed rate and composition
  - (b) reflux rate
  - (c) feed and reflux temperatures
  - (d) heat input rate
  - (e) reflux drum and reboiler holdups

Of these only the flow rate measurements were not particularly accurate. Since the column response is relatively more sensitive to these variables than others, they are suspected to have made the largest contributions to the discrepancy between the predicted and actual temperatures

- (ii) the inaccuracies in the prediction of tray efficiencies which is partly due to the fact

that the physical properties are all determined by predictive methods

- (iii) the inaccuracies of the estimation of heat losses
- (iv) the assumption of 100 per cent equilibrium efficiency at the reboiler. A more exact value obtained experimentally would have produced better results
- (v) the assumption of constant pressure is not strictly true. The pressure at the reboiler is higher than the top. Two pressure measurements would enable better comparison

Since the holdups in the reflux drum and the reboiler are considerably larger than that of a typical tray, it was not unrealistic to assume perfect level control at these points which is again consistent with the philosophy of replacing the differential equations by their steady-state approximations when possible. In practice, tight level controllers will enable the levels to remain almost constant and because of large holdups, the minor variations in them are ironed out.

#### IX.4 ESTIMATION

The proposed methodology for the extension of the linear Kalman filter to nonlinear systems appears to have overcome the typical stability problems reported in the literature. Chemical engineering systems as nonlinear as distillation with highly nonlinear measurement functional relationships are rare - although a few pathological cases may be cited. Therefore, it is questionable whether further extension of linear filtering theory such as adaptive filtering is justifiable for chemical processes - especially in complex high dimensionality systems.

As regards the binary distillation case, the performance of the filter model (Model I based on mass balances only) has been compared with that of the column simulator (Model II) in Chapter V. It can be seen that the filter model predictions are very inaccurate. The assumption of ideality has also been made in the derivation of the filter model for the measurement relationships which is again inaccurate. Despite these inbuilt approximations in the filter models, the measurement noise and the erratic deterministic disturbances of known and unknown natures, the extended Kalman filters formulated in this research produced accurate estimates of the state of the column from a handful of corrupt temperature measurements with sample times of up to 40 seconds. The filters were also insensitive to the integration method

used for predictions. They were equally accurate and stable with the simple Euler while the column simulator was being integrated by the fourth-order Runge-Kutta method - the step sizes being equal.

Dynamic simulation studies with the column simulator and extensive print-outs have pointed to the fact that the assumption of constant tray holdups does not appear to be unreasonable. Therefore, the order of the filter's system model can be decreased by a half if it is formulated based on this assumption. This means less intersample calculations, hence smaller sample times and more accurate estimates. This can be an important corollary especially in larger columns where adequate low order filter models are needed.

Finally, the ability of extended Kalman filters to function as fast and accurate on-line analysers opens interesting possibilities for overcoming hardware problems by the relatively inexpensive software approach - especially in relation to control.

## IX.5 ESTIMATOR-AIDED FEEDFORWARD CONTROL

The simulation results have shown that the performance of EAFF control is superior to feedback temperature control in that

- (i) when the column is subjected to a sustained step increase in the feed rate, the controlled variables undergo less transients and take far less time to return to their desired setpoints (see Figures VIII.5 and VIII.6)
- (ii) the IAE for EAFF control is half as much as that for feedback temperature control even when the feedback controllers are tightly tuned
- (iii) when the column was subjected to multiple disturbances under feedback temperature control in a subsequent experiment (see Figures VIII.9 and VIII.10), the column became unstable pointing to the fact that the tuning of these controllers was too tight in the previous experiment to make their associated IAE, used for comparison with that of EAFF control, representative and meaningful. In real life one would not risk tuning the controllers so tightly and, therefore a much larger IAE would be expected. Even under these conditions, the performance of EAFF control was twice as good as feedback control.
- (iv) EAFF control appears to be more efficient in terms of finding the right targets for the

manipulated variables (Figures VIII.7, VIII.8, VIII.11 and VIII.12) when known and unknown disturbances do occur. This primarily means that EAFF control minimizes the typical interaction problems experienced with feedback control. This is to be expected because of its self-corrective nature. Secondly, in terms of energy consumption and producing less off-specification compositions, EAFF control is superior to feedback temperature control

Therefore, EAFF control may offer a plausible approach to meeting the recent criticisms raised against the status of chemical process control.

In the example used as the test case, the same model was used for predicting the state variables for estimation and for control. If, however, having calculated the predicted state at the next sample time and having computed the control inputs, the filter's system model is reintegrated with the new values of the control inputs for estimation, the state estimation should be more accurate and so should the control. Obviously, this proposal can only be implemented if there is sufficient time in between samples to perform the state predictions twice, once for control and once for estimation.

Another important consideration in the design of extended Kalman filters for EAFF control is that all of the control inputs should be estimated as parameters and measured if possible.



## IX.6 RECOMMENDATIONS FOR FURTHER WORK

As regards hardware modifications to the distillation column a number of proposals have already been made.

As far as the theoretical proposals are concerned, and in relation to distillation, the logical extension of this work would be to test these ideas on multicomponent distillation whether they be related to simulation, estimation or control.

EAFF control could be tested on other well-understood multivariable systems such as chemical reactors with controllers preferably designed by a multivariable feedforward design method. The publications of the University of Alberta in Canada (102) provide a good survey of the available multivariable design methods.

A P P E N D I X A

## A.1 THE CHARACTERISTICS OF THE MOTORIZED VALVES

The valve positions have been tabulated against their corresponding digital output channel numbers in the following table.

Digital-Output Channel Number	Position of the Valve	Characteristic Figure Number
1	Reflux	A.1.1
2	Bottoms	A.1.2
3	Feed	A.1.3
4	Distillate	A.1.4
5	Condenser cooling water	Not studied

The characteristic equations are given in Chapter III, in Table III.3.

Figure A.1.1

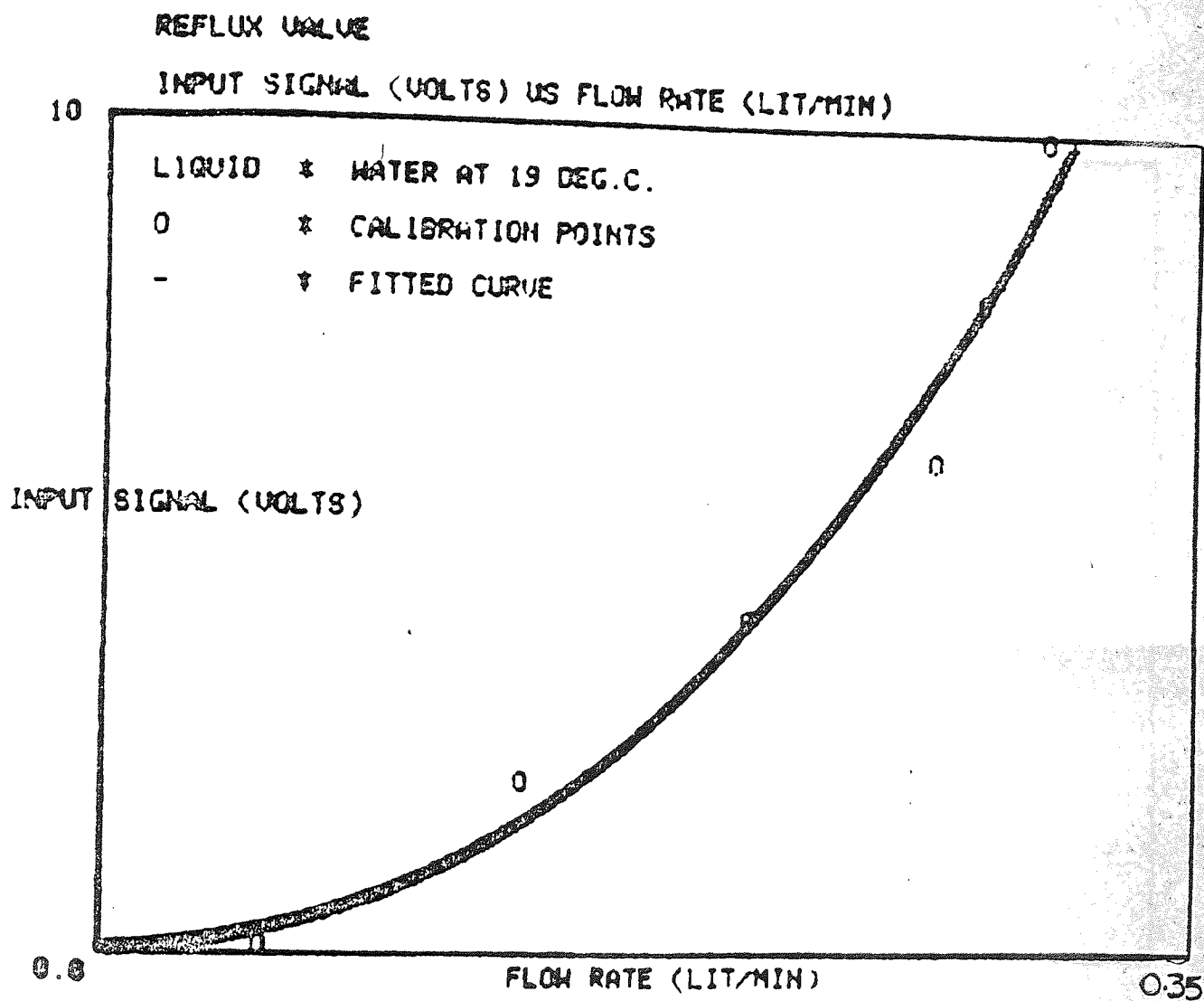


Figure A.1.2

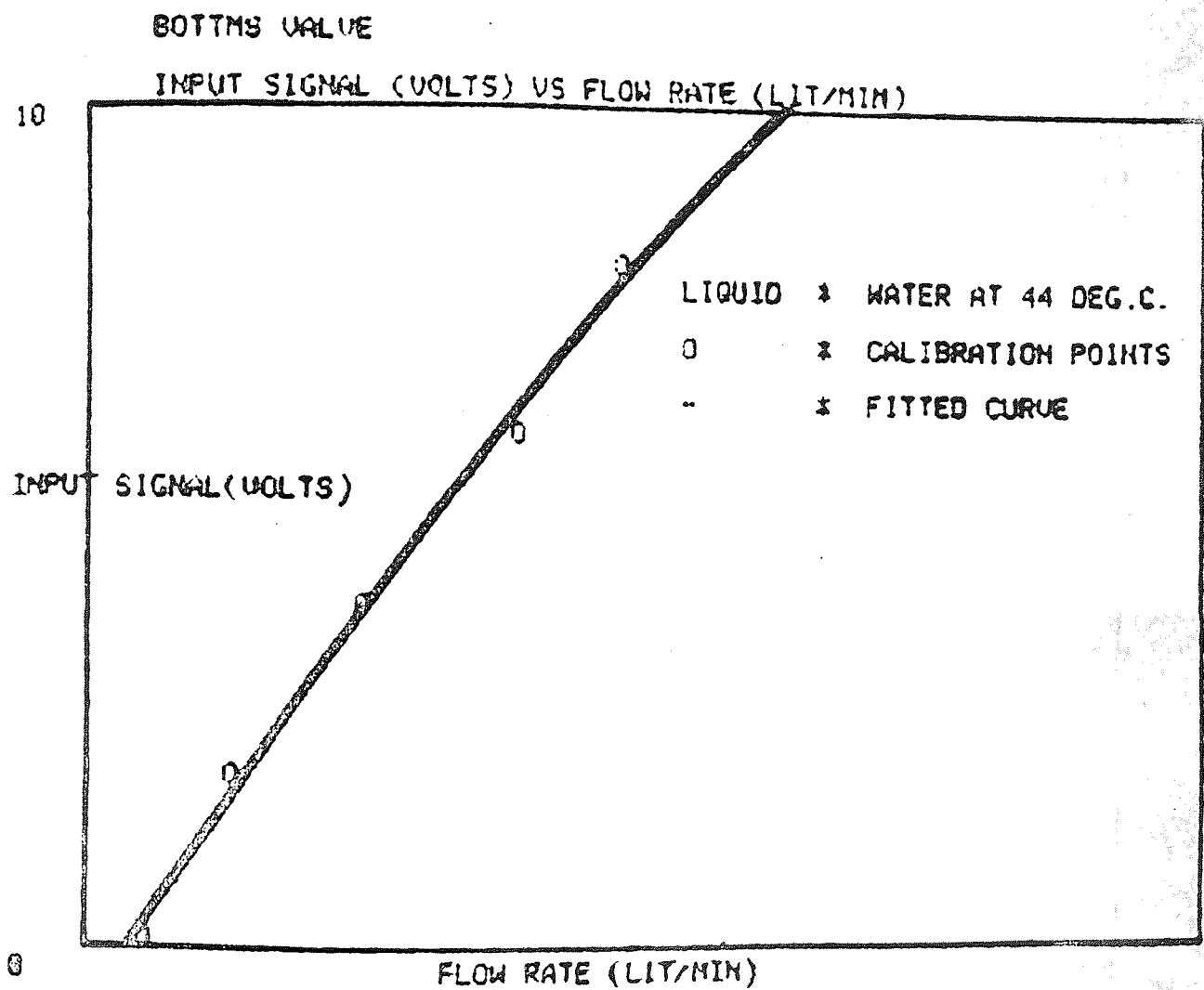


Figure A.1.3

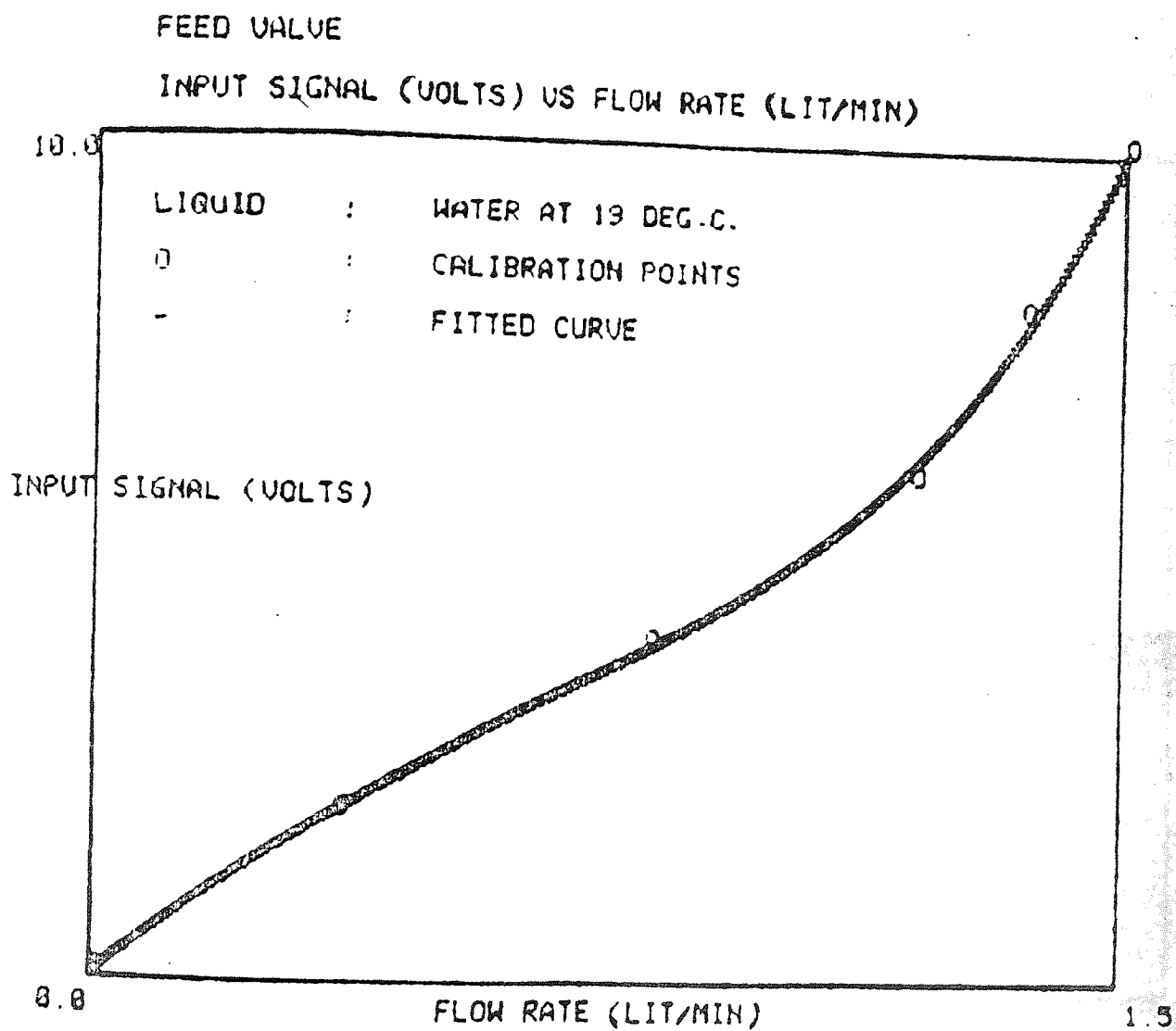
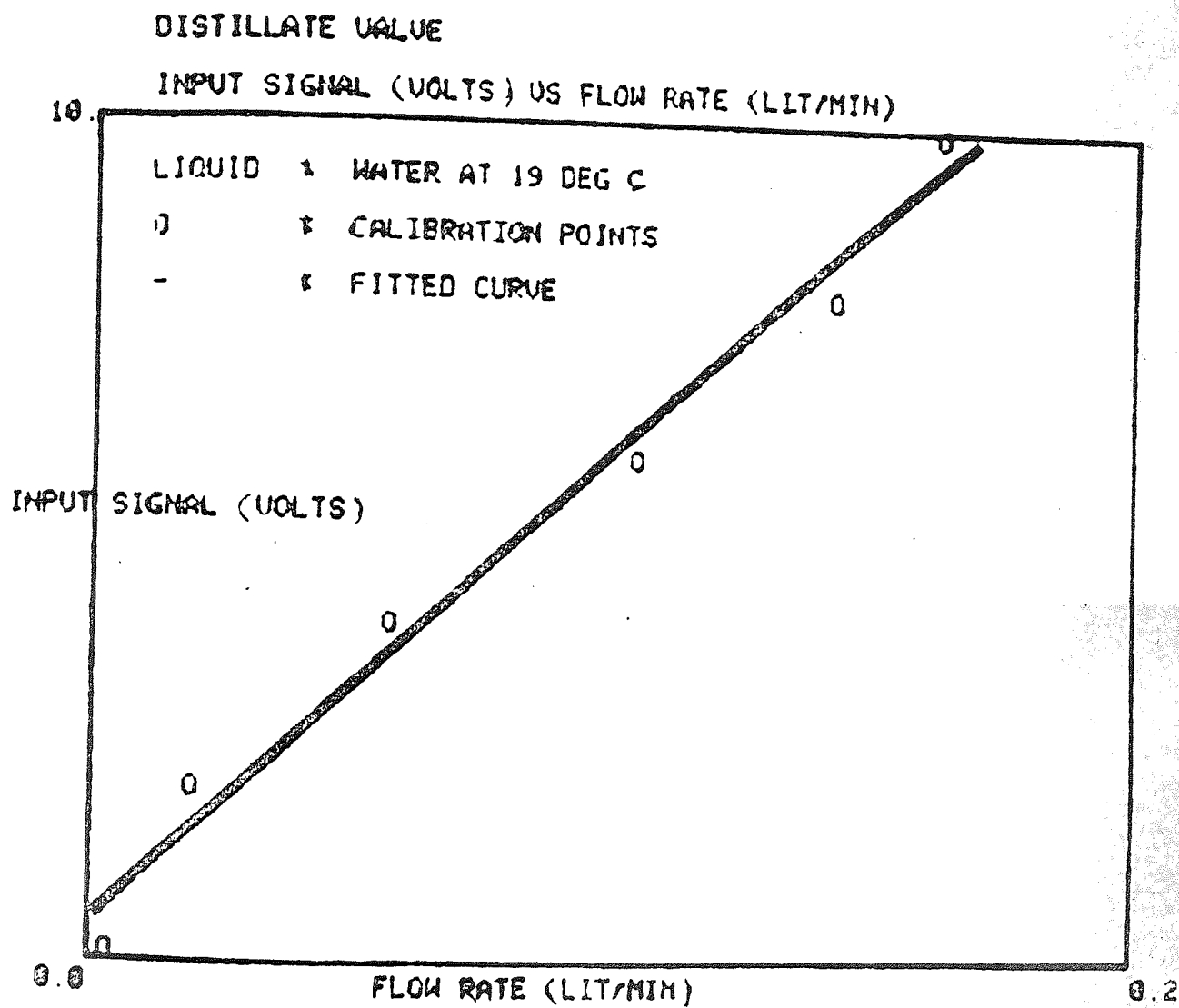


Figure A.1.4





## A.2 THE REBOILER CHARACTERISTICS

The digital output channel number 6 corresponds to the reboiler. The characteristic curves for the reboiler are as follows:

Figure A.2.1 :  $Q_{12}$  vs input signal

Figure A.2.2 : input signal vs  $Q_{12}$

Figure A.2.3 : heat transfer rate vs mass of liquid  
in the reboiler

Figure A.2.4 :  $R = \frac{Q_{12}}{Q_A}$  vs mass of liquid in the  
reboiler

where

$Q_A$  = actual heat transfer rate

$Q_{12}$  = heat transfer rate when the reboiler holdup is  
12 kg.

Figure A.2.1

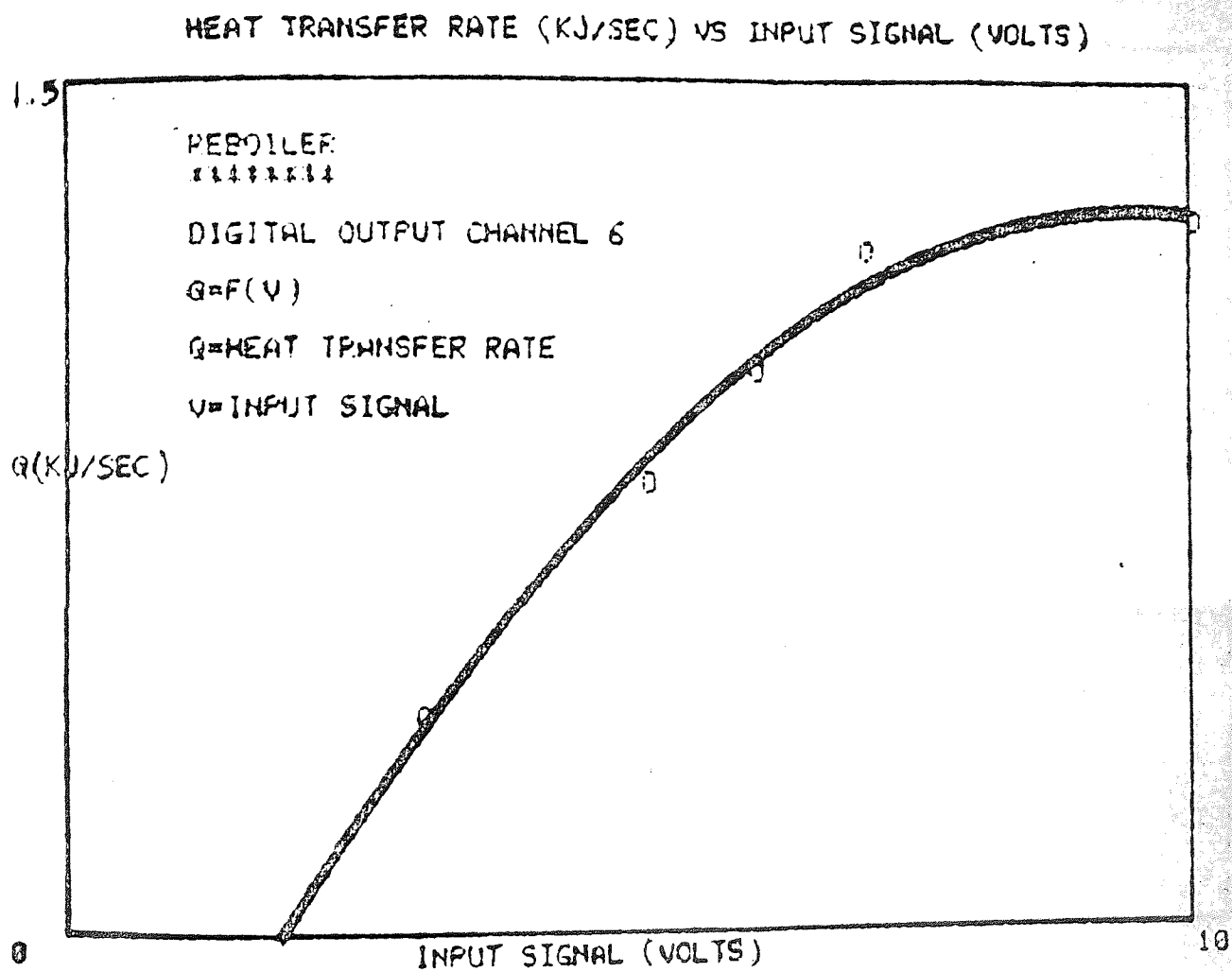


Figure A.2.2

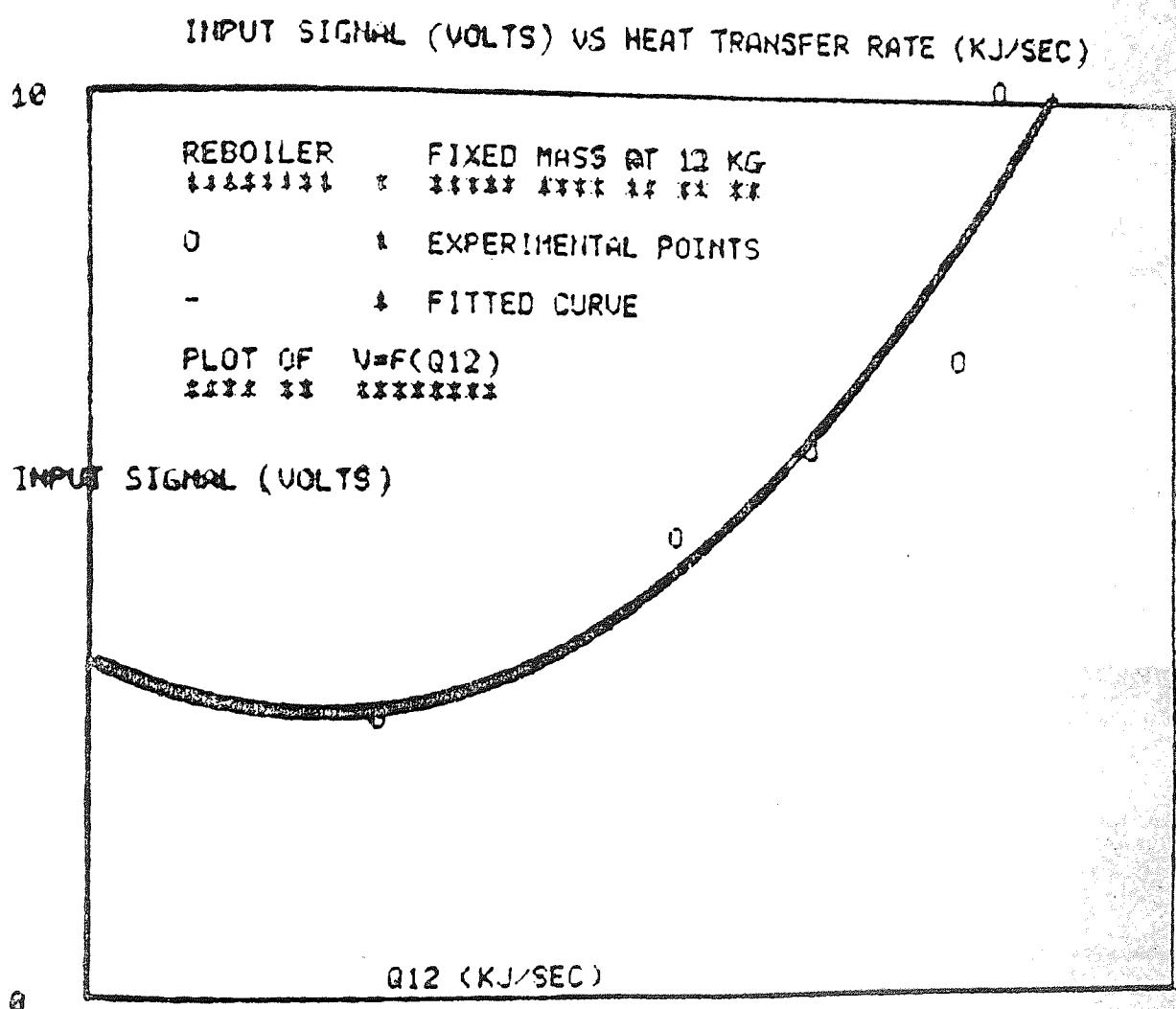


Figure A.2.3

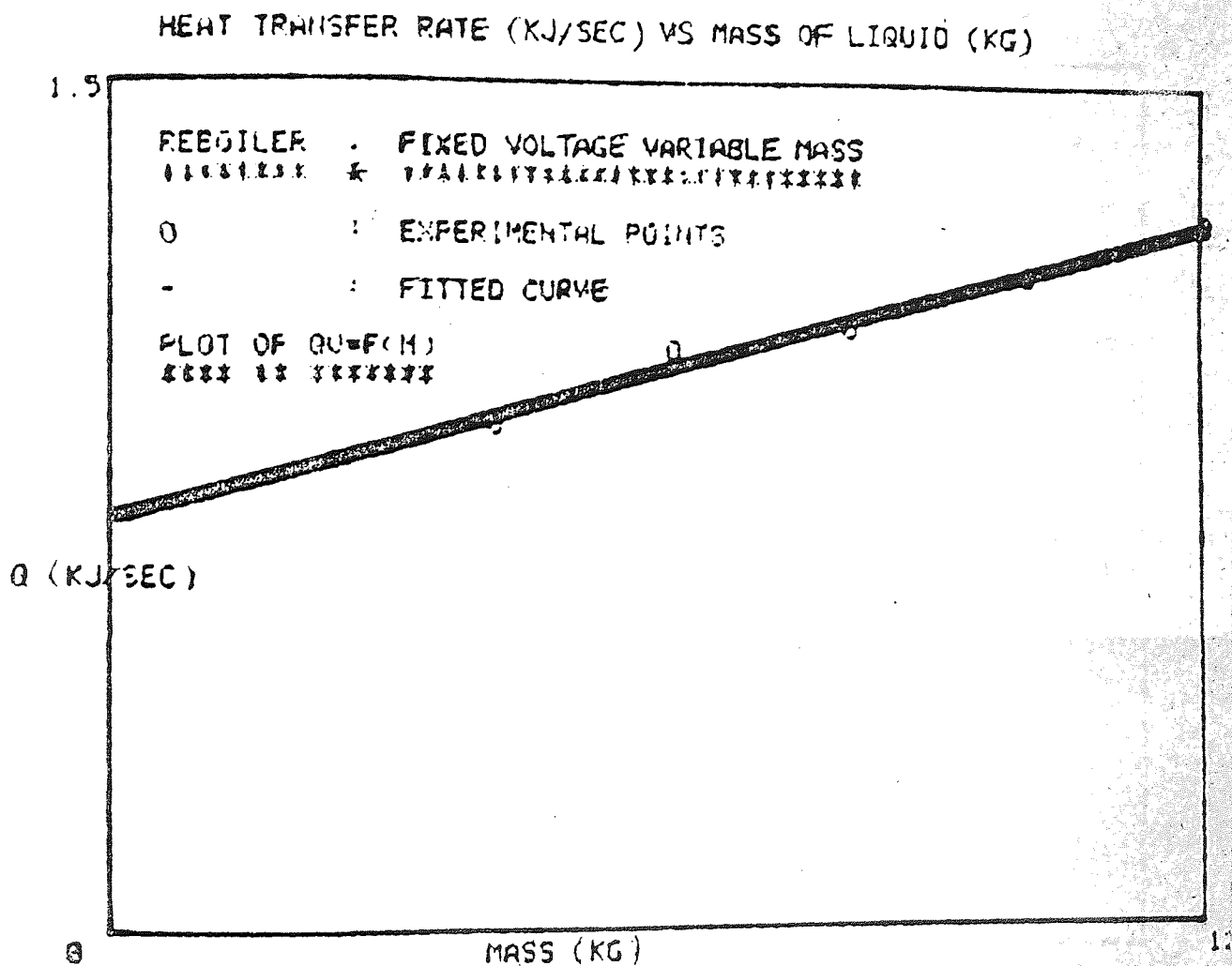
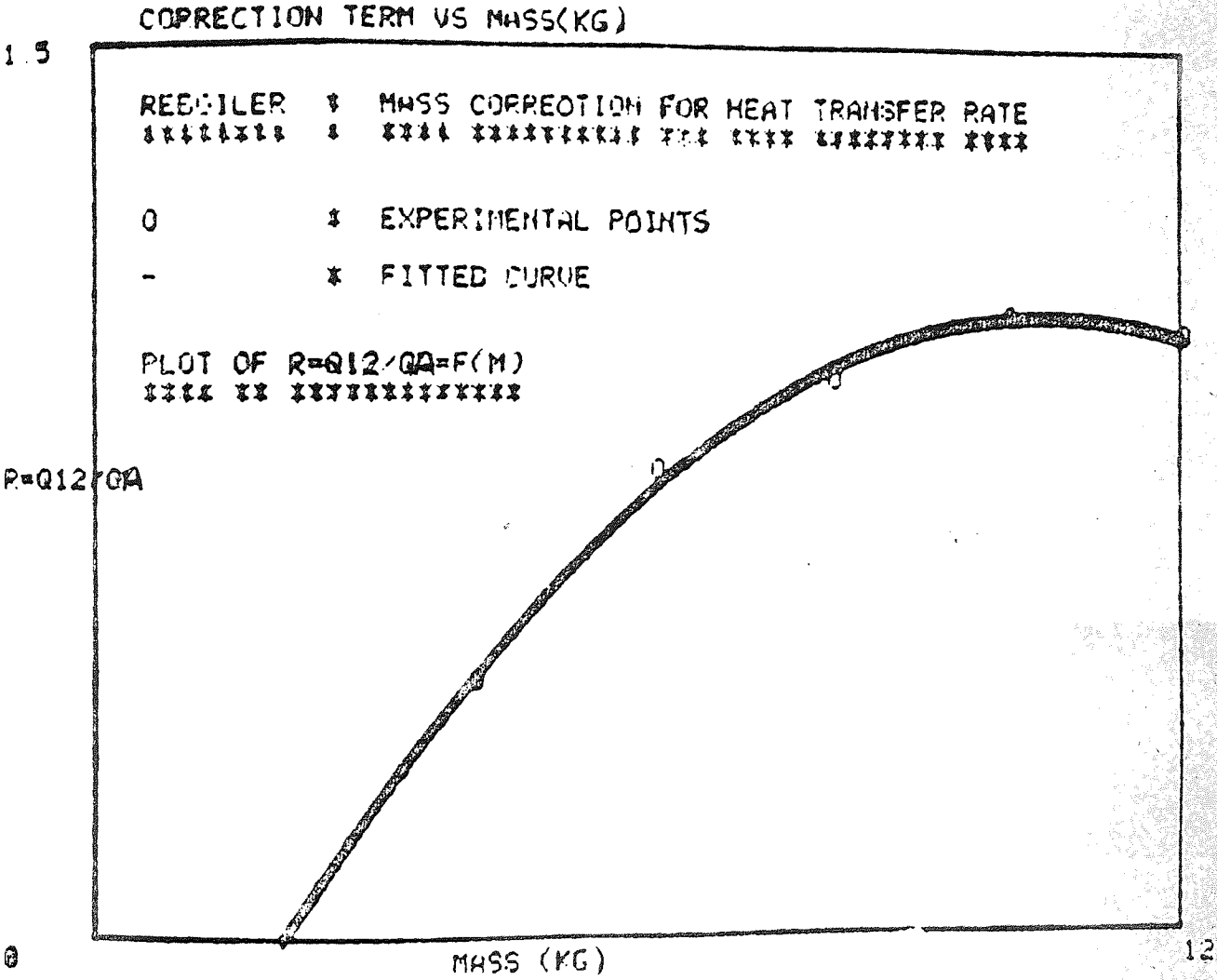


Figure A.2.4



### A.3 THE THERMOCOUPLE CHARACTERISTICS

The characteristic equations have been given in Chapter III.

Figure Number	Correlated Variables	Process Variable Measured
A.3.1	T vs V	Top tray temperature
A.3.1	T vs V	Feed tray temperature
A.3.2	T vs V	Bottom tray temperature

where T denotes temperature in  $^{\circ}\text{C}$ .

V refers to output voltage from the thermocouple  
in volts.

Figure A.3.1

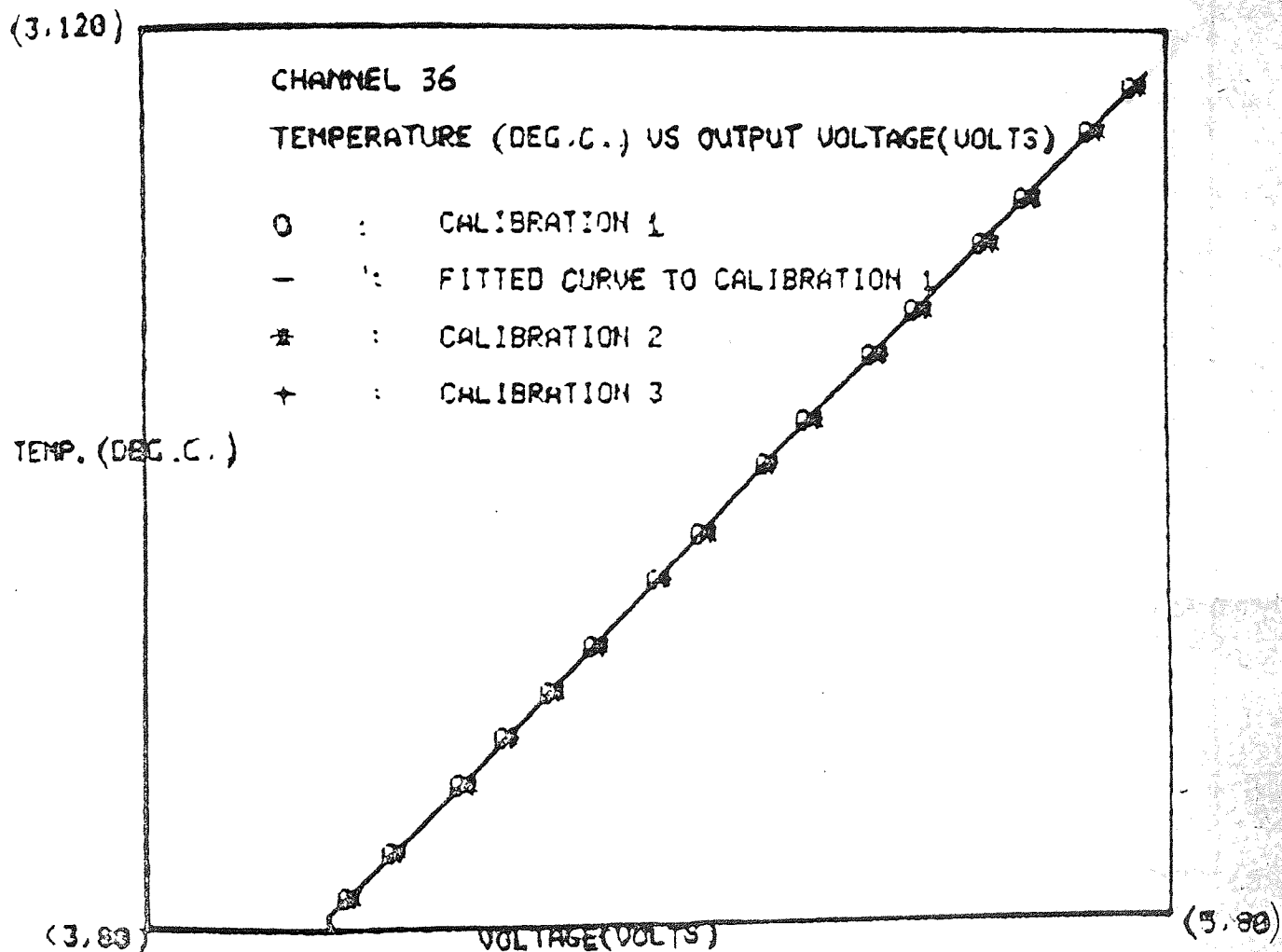




Figure A.3.2

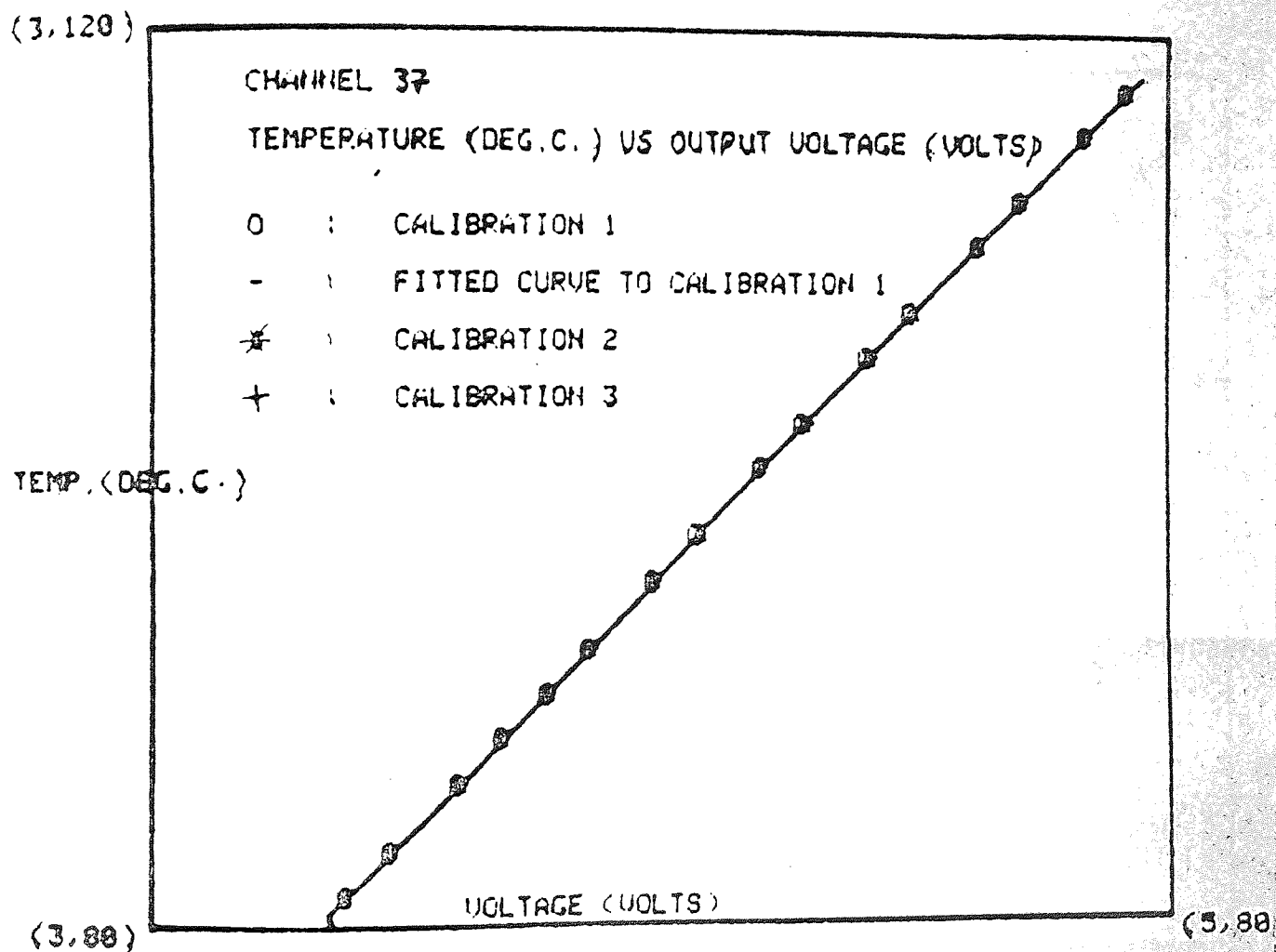
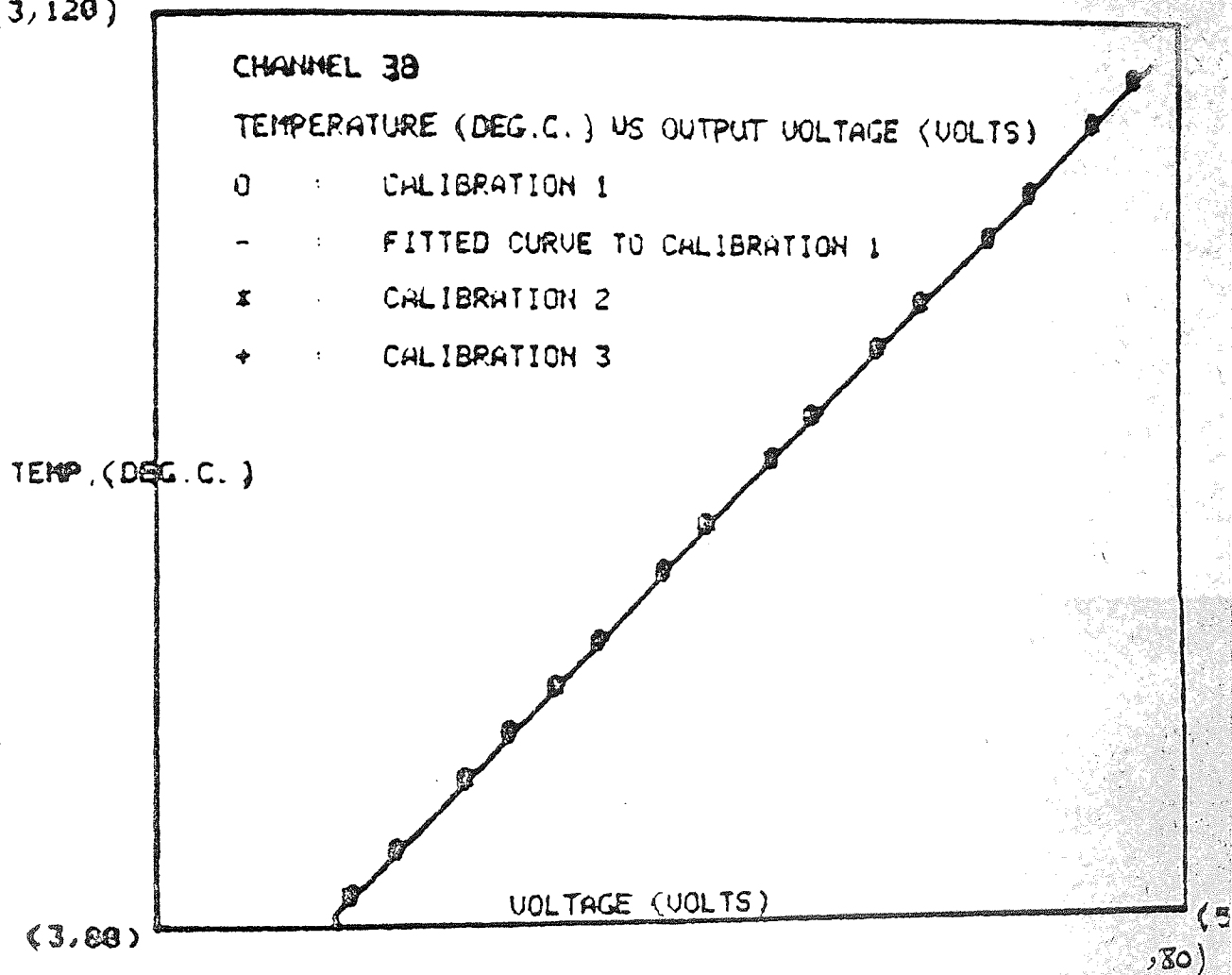


Figure A.3.3

(3,120)



#### A.4 THE CHARACTERISTICS OF THE LEVEL-INDICATORS

Figure A.4.1 : The reflux drum level indicator

Figure A.4.2 : The reboiler level-indicator

Figure A.4.1

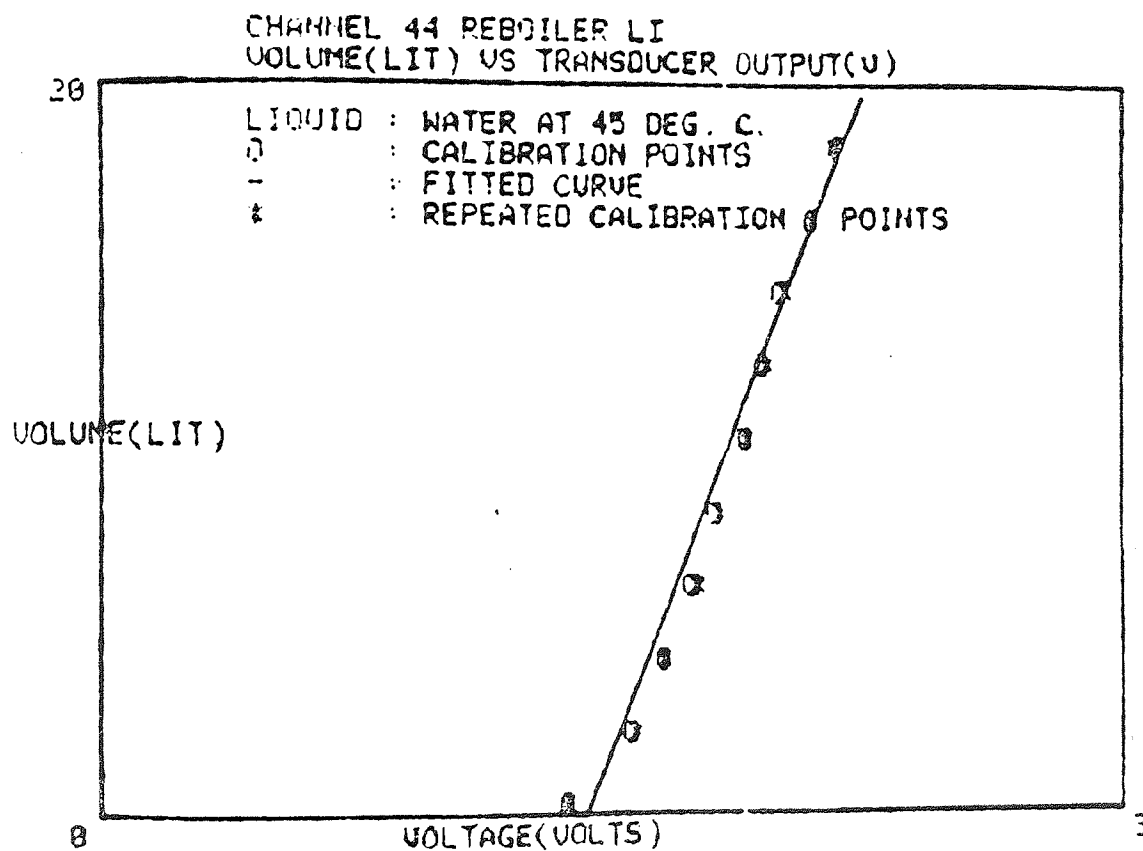
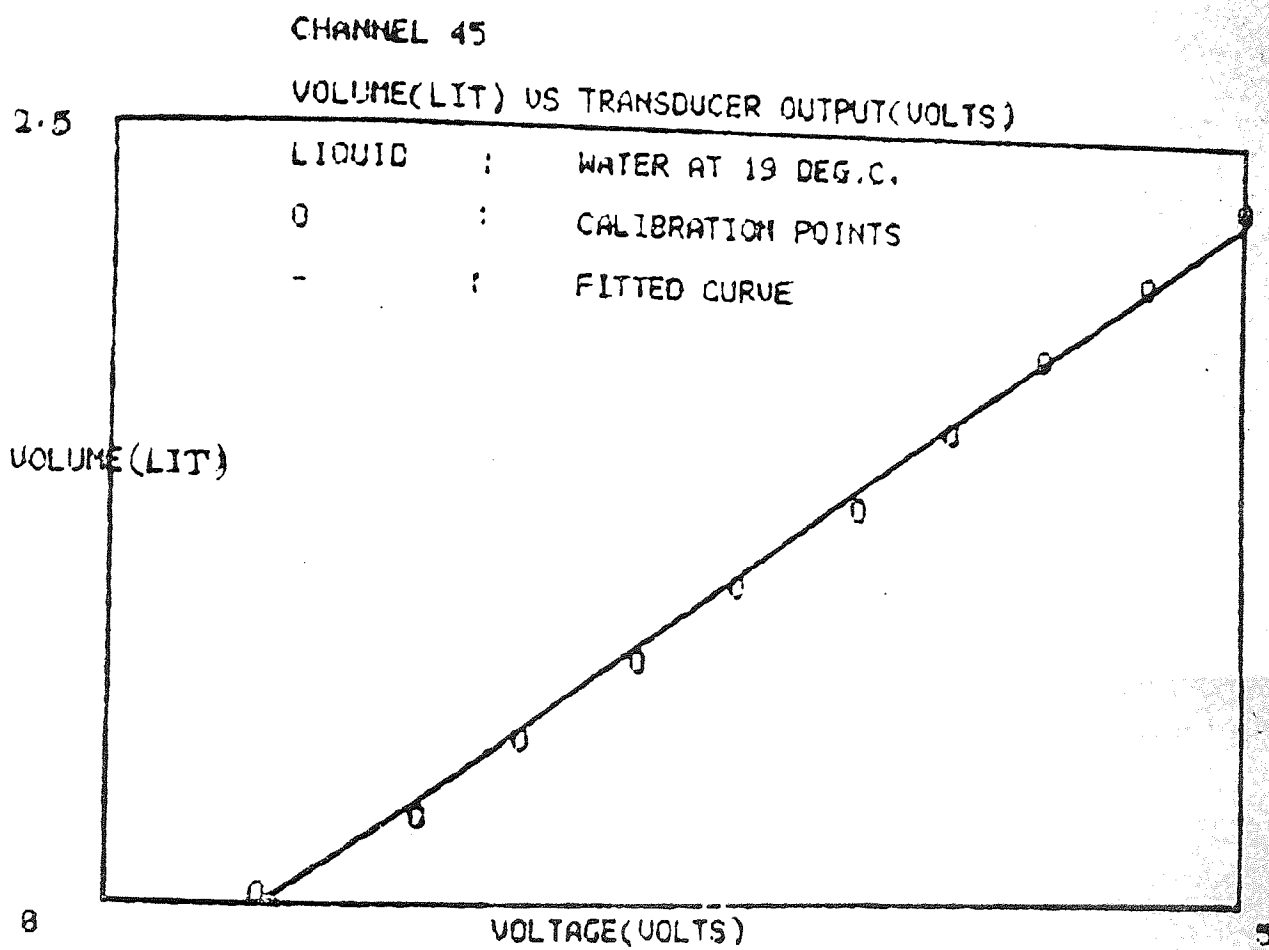


Figure A.4.2



## A.5 THE FLOW MEASUREMENT TRANSDUCER CHARACTERISTICS

Figure A.5.1 : feed rate measurement

Figure A.5.2 : bottoms measurement

Figure A.5.3 : distillate measurement

Figure A.5.4 : reflux rate measurement

### A.5.1 THE ORIFICE PLATE HOLE SIZES

Measurement	Orifice Size
Feed	1.8 mm
Bottoms	2.0 mm
Distillate	1.3 mm
Reflux	1.3 mm
Condenser cooling water	5.0 mm

The sizes of the orifice holes have been chosen by trial and error. The following considerations are instrumental in the choice of these hole sizes:

- (i) they must be small enough to give the right sensitivity
- (ii) they have to be sufficiently large in order not to flood the transducers at the maximum openings of their associated motorized valves

### A.5.2 CALIBRATION EQUATIONS

The form of the correlation is

$$F = a + bv + cv^2 + dv^3$$

where

F = flow rate                      cc./min.

v = transducer output volts

$\alpha$  = correlation coefficients

a,b,c,d = constants

The polynomial coefficients are tabulated below.

Flow	a	b	c	d	$\alpha$
Reflux	-10.2	81.9	-	-	0.91
Bottoms	46.2	135.0	-	-	0.94
Feed	-128	590	-75.4	-	0.97
Distillate	-44.62	123.3	-26.87	2.409	0.92

The curve-fittings were done by the least squares method.



Figure A.5.1

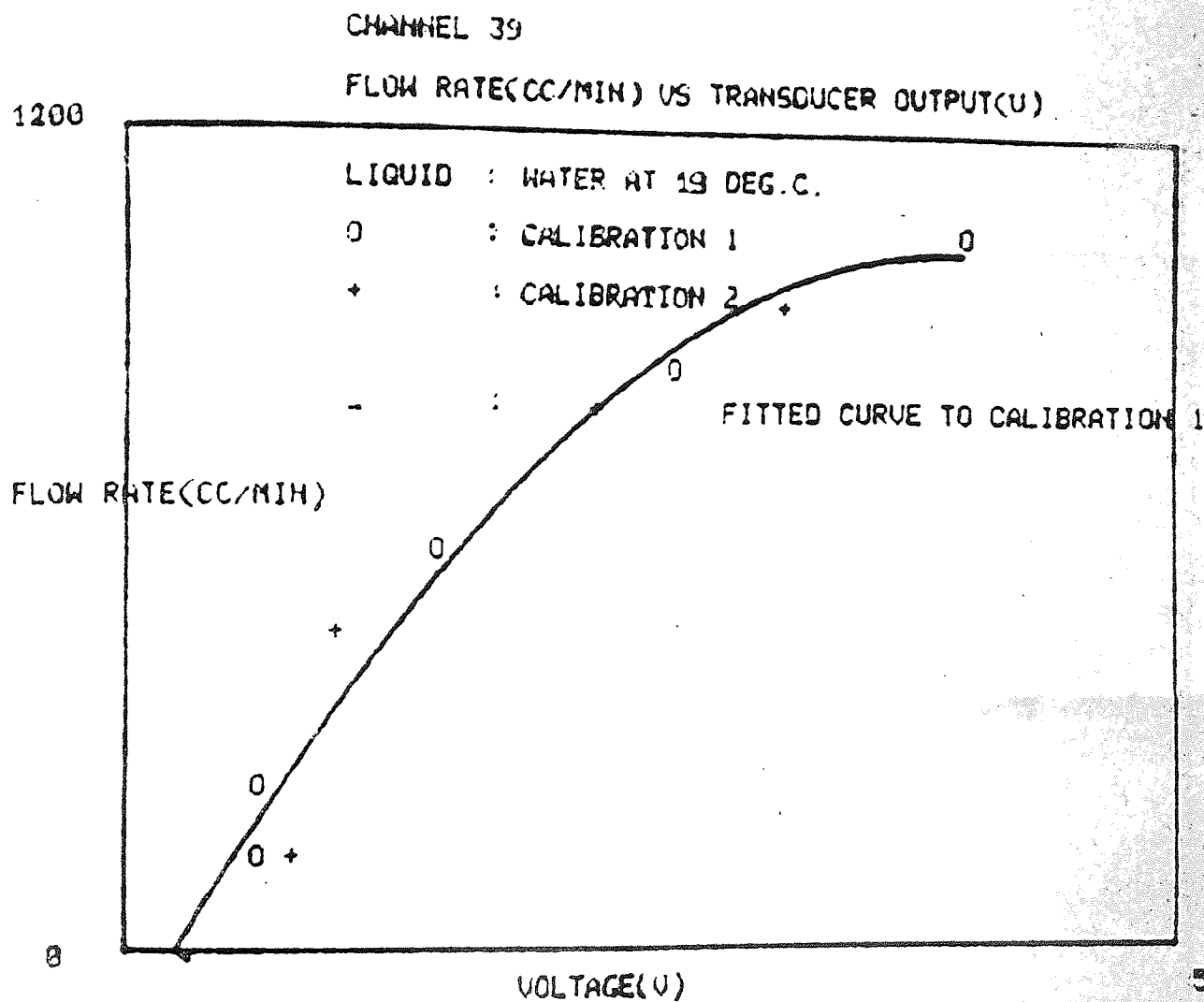


Figure A.5.2

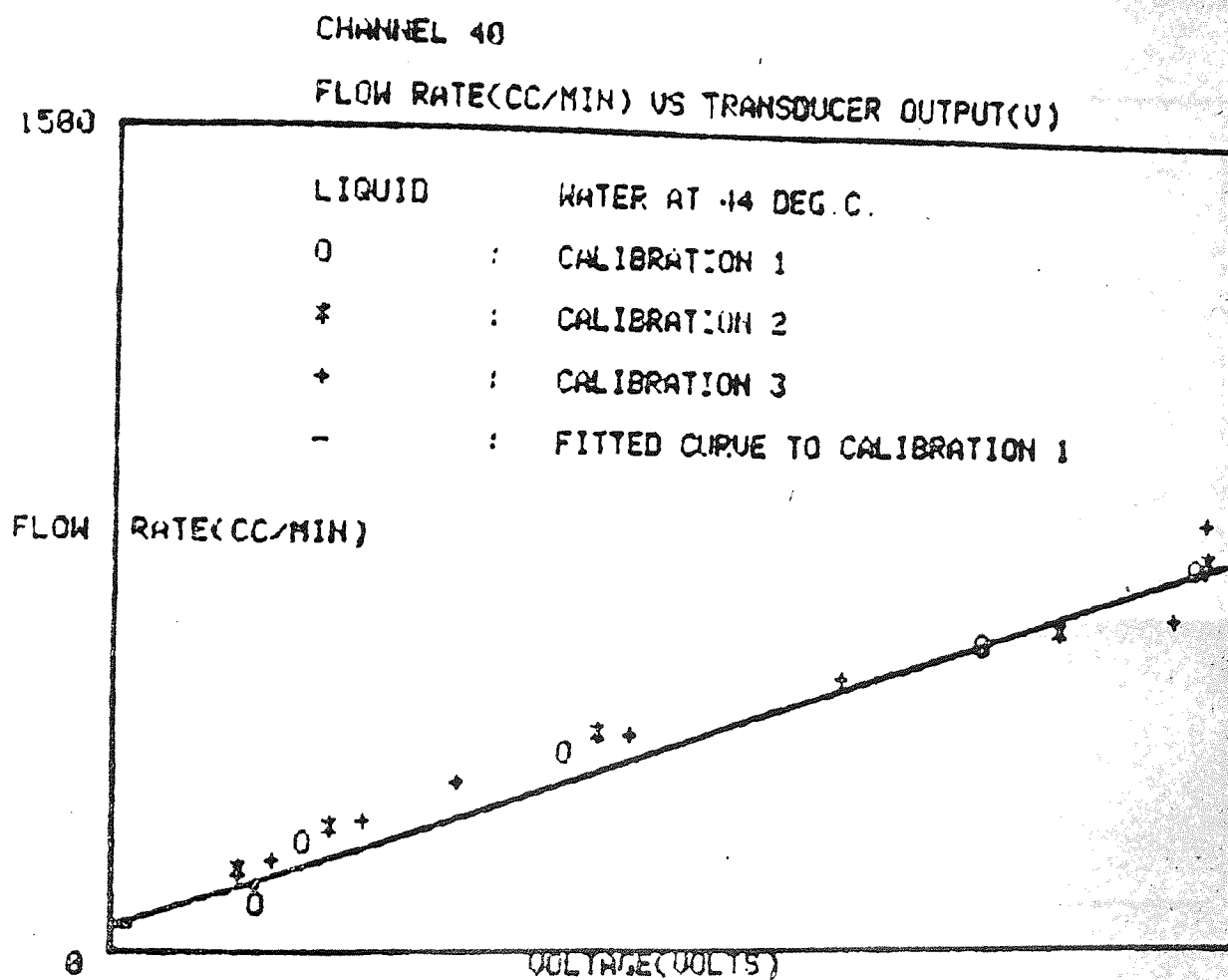


Figure A.5.3

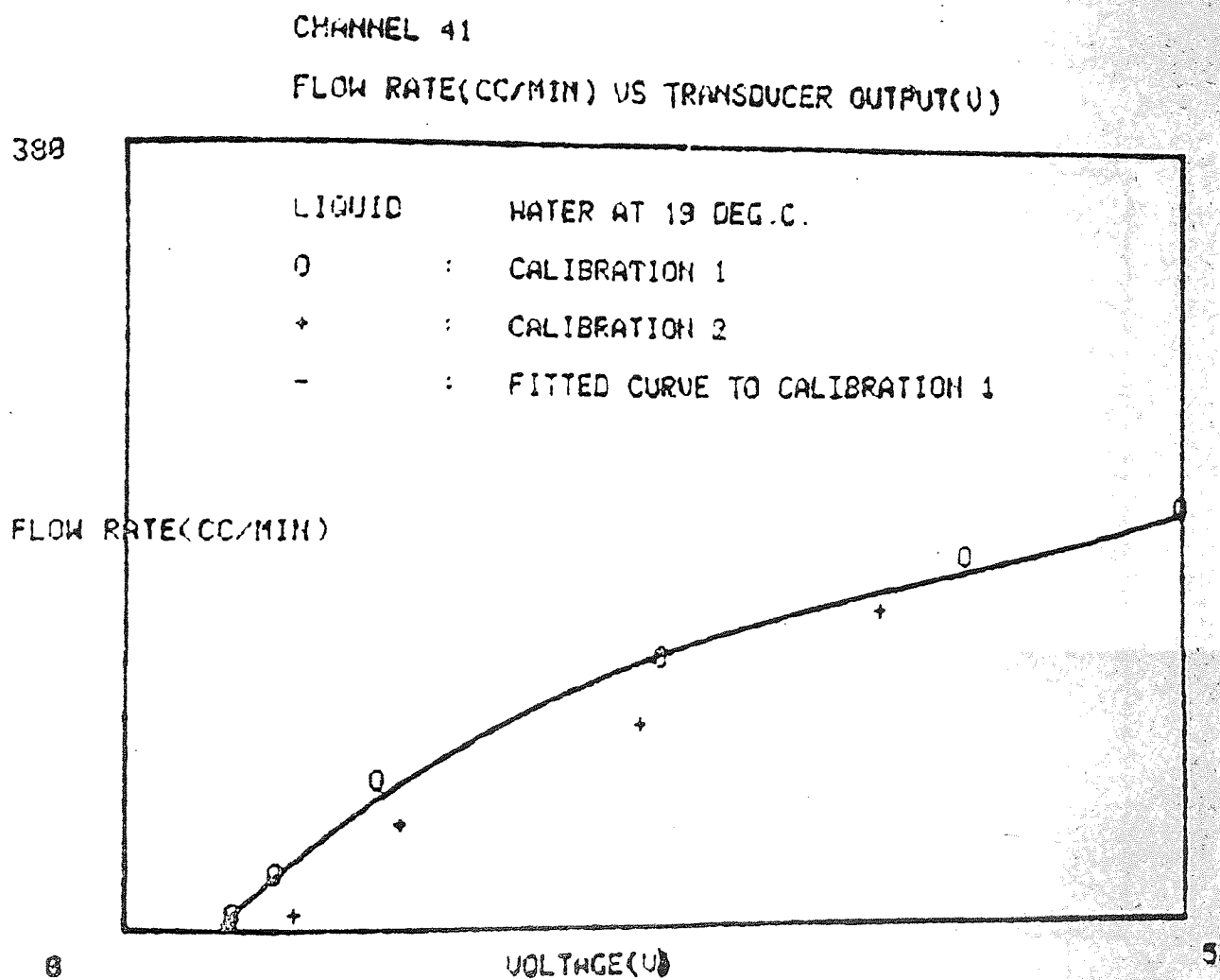
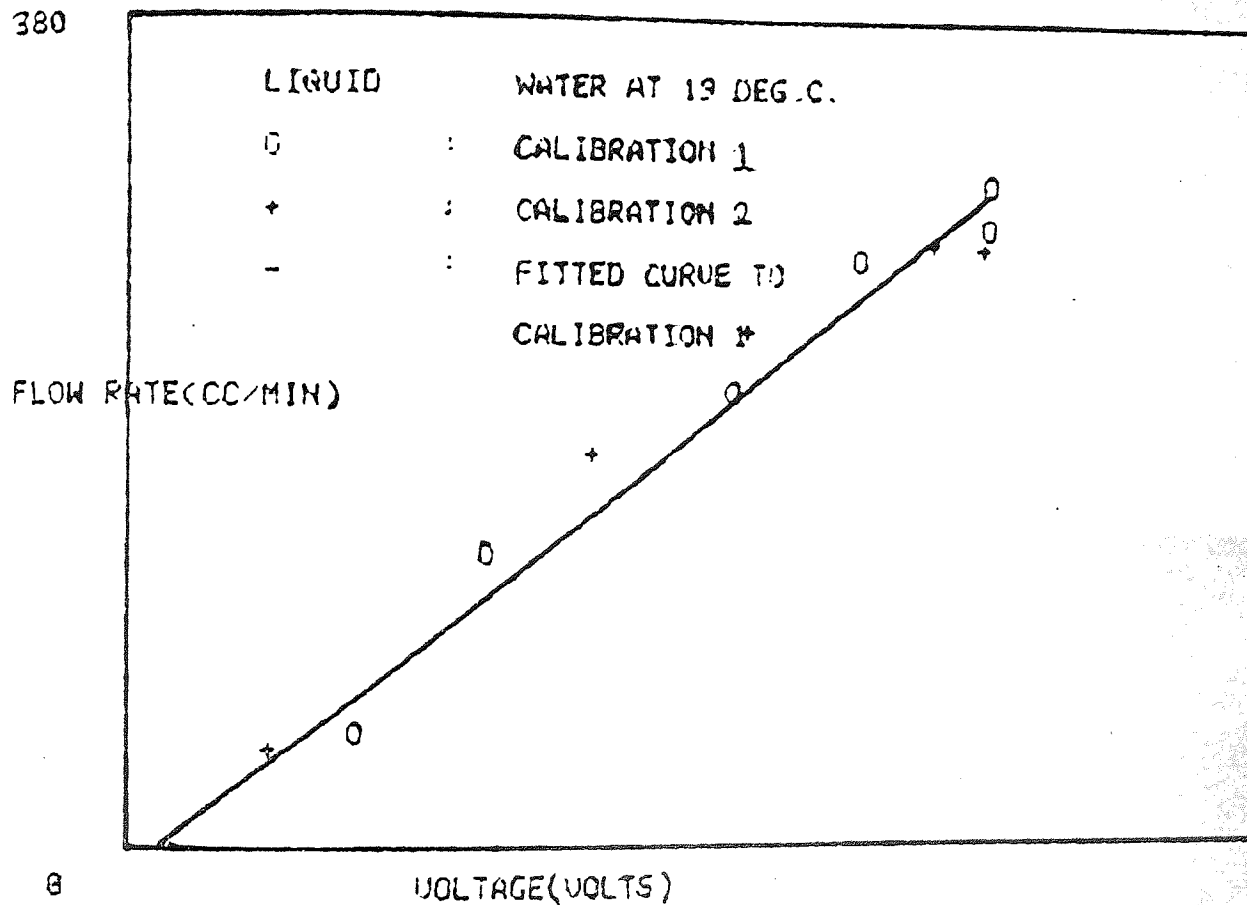


Figure A.5.4

CHANNEL 42

FLOW RATE(CC/MIN) VS TRANSDUCER OUTPUT(V)

380



A P P E N D I X   B

## B.1 THE PROPOSED STRUCTURE FOR A PROCESS SIMULATOR

In a dynamic simulator, next to the mathematical modelling aspects, the role of the structure relative to that of the integrator is of central importance and has considerable bearing on the flexibility of the simulator. Unfortunately, most, if not all, of the available integrators require that a structure be set up in a predefined manner and that once the integrator is called, it will then take control of the operations without allowing any further user interference until the simulation is finished. In other words, the structure is subordinate to the integrator and must be designed to suit the integrator. This arrangement can be somewhat limiting and cumbersome since, ideally, one would like an integrator that can be called autonomously at any point within the structure to update any number of variables and report back at the end of any number of steps. Additionally, it is often helpful if the independent variable is advanced outside the integrator as the user desires as opposed to its being advanced by the integrator. This aspect can enhance the flexibility of the simulator especially for on-line applications where the chances of missing a sample or a control point will practically be zero since the user will have full control over advancing the time.

In order to enable the user to devise such a structure to suit his needs, a collection of four FORTRAN subroutines are proposed which are, namely,

SDINT, INTJS, INTPAS, and PRINT. Due to the important role of the integrator, some elaboration on the functions to be performed by these subroutines and an example of how the main program structure may be set up to communicate with this integrator will be in order at this stage.

#### SUBROUTINE SDINT

This subroutine carries out the integration and offers a choice of three different integration methods which are first-, second- and fourth-order respectively. These are as follows:

- (i) the Euler method
- (ii) the Euler predictor-corrector method
- (iii) the Runge-Kutta method

Experience with a wide range of typical chemical engineering problems has shown that with almost no exception, the fourth-order Runge-Kutta method is quite adequate for any situation but the second- and first-order methods are also alternatives that can provide reasonable accuracy coupled with greater computational efficiency when short step sizes are forced on the Runge-Kutta.

The formal variables of this subroutine are:

- (i) XX and DX; which contain the values of the integrated variable and its derivative respectively
- (ii) TD; which represents the independent variable
- (iii) DTD; which is the integration step size
- (iv) IOD; which stands for the order of the integration



method

- (v) INTCAL; when a set of differential equations are being solved simultaneously, this variable signals to the integrator which variable is being integrated so that the inter-step information corresponding to that variable can be identified in the higher order methods where more than one derivative evaluation is needed in each integration step

The common variables of this subroutine held in the COMMON block labelled INTEG are:

- (i) JE; the integrator pass number for the Euler's method
- (ii) JS; the pass number for the predictor-corrector method specifying whether the calculation is performing its first or second derivative evaluation
- (iii) JS4; the pass number for the fourth-order Runge-Kutta method
- (iv) ND; the total number of differential equations

#### SUBROUTINE INTJS

When a set of differential equations are being solved simultaneously, the function of this subroutine is to ensure that all of the dependent integrated variables are updated before the integrator pass number is advanced in the higher order integration methods (the predictor-corrector and Runge-Kutta fourth order).

The formal variables of this subroutine are:

- (i) JS4, JS, JE and ND; as defined before.
- (ii) IPASS; which is a flag for checking for the step completion in the higher order methods and is controlled by subroutine INTPAS. E.g. when JS4 is greater than 4, IPASS will be set to zero.

The common variables are as those defined for the subroutine SDINT.

#### SUBROUTINE PRINT

The purpose of this subroutine is to print variables of interest and also to control the frequency of printing. The number of variables that need to be printed is a problem-dependent consideration. These variables can be transferred to the subroutine through the argument list, or otherwise, and the corresponding WRITE statement can then be modified accordingly. This subprogram also safeguards against printing redundant interstep information by checking the integration pass numbers JS and JS4 when higher order integration methods are being used.

The formal variables of this subroutine are:

- (i) T; is the independent variable
- (ii) DT; is the integration step length
- (iii) PI; is the print interval which should be equal to  $N \cdot DT$  with N being an integer
- (iv) plus any other variable of interest that needs to be printed out.

### AN EXAMPLE

Consider a system represented by the following differential equation:

$$\ddot{y} + y = 0; \quad t=0, \dot{y}(0)=1.0, y(0)=0$$

This equation can be reduced to a set of two first order differential equations which can then be solved simultaneously. The program listing that follows shows the main program arrangement required to simulate this system and also the layout of the subprogram named DYMOD where the actual simulation takes place. This particular problem happens to have an analytical solution as well which is evaluated in subroutine ANMOD to enable comparison between the analytical and numerical solutions. The results are shown in Table B.1. As expected, for the same step size, higher order integration methods provide better accuracy.

## GENERAL ARRANGEMENT OF THE MAIN PROGRAM FOR THE USE OF SDINT SUBROUTINES

The main program arrangement is depicted in Figure IV.1 in Chapter IV. Following a preliminary housekeeping section containing FORMATS and DECLARATION statements, the initialization section is laid out. Here all the calculations and specification for the problem parameters and coefficients are made. These are the values that are normally invariant during the course of the calculations. In this section, the initial conditions for the integrated variables must also be specified. The next section is the dynamic section in which the individual simulator modules are called to perform the simulation and the independent variable is advanced when all the modules have been updated.

## THE PROGRAM ARRANGEMENT FOR THE INDIVIDUAL SIMULATOR MODULES

The individual simulator modules must be laid out according to the flowchart shown in Figure IV.2.

Each module essentially comprises:

- (i) the preliminary calculation section (if necessary)
- (ii) the derivative section in which the derivatives are defined
- (iii) the integration section where the dependent variables are updated
- (iv) the test for the step completion and a CALL to the subroutine INTPAS to zero the integrator pass numbers for the next step

```

C: ::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
C: PROGRAM TO TEST THE FIXED STEP INTEGRATOR AND THE
C: PROPOSED STRUCTURE
C: EXAMPLE 1 ; SOLUTION OF A 2ND ORDER O.D.E
C: *** SYMBOLS ***
C: Z=VECTOR OF SOLUTIONS FOUND BY NUMERICAL INTEGRATION:
C: AZ=VECTOR OF ANALYTICAL SOLUTIONS
C: DZ=VECTOR OF DERIVATIVES
C: TIME=THE INDEPENDENT VARIABLE
C: PI=PRINT INTERVAL ; AN INTEGER MULTIPLE OF DT
C: DT=STEP LENGTH
C: IPASS=INTEGRATOR PASS NUMBER
C: IOD=INTEGRATION ORDER
C: =1 EULER
C: =2 PREDICTOR CORRECTOR
C: =4 RUNGE-KUTTA FOURTH ORDER
C: JE=FLAG FOR STEP COMPLETION IN EULER
C: JS=FLAG FOR STEP COMPLETION IN PREDICTOR-CORRECTOR
C: JS4=FLAG FOR STEP COMPLETION IN RUNGE-KUTTA
C: ND=NUMBER OF DIFFERENTIAL EQUATION IN EACH MODULE
C: ANMOD=SIMULATOR MODULE USING ANALYTICAL SOLUTIONS
C: DYMOD=SIMULATOR MODULE USING NUMERICAL SOLUTIONS
C: ::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
COMMON/MODEL/Z(2),AZ(2),DZ(2),A,B
COMMON/INTEG/JS4,JS,JE,ND
C**** INFORMATION NEEDED FOR THE INTEGRATOR
JE=0
JS=0
JS4=0
READ(1,100) DT,PI,ENDT,IOD
100 FORMAT(3F0.0,1I0)
ND=2
IPASS=0
C**** CONSTANTS
READ(1,200) A,B
200 FORMAT(2F0.0)
C**** INITIALIZATION
TIME=0.
Z(1)=0.
Z(2)=1.
AZ(1)=0.
C**** PRINT TITLE
WRITE(2,1)
1 FORMAT(3X,'TIME',8X,'AZ',8X,'Z',8X,'ERROR'/
+ , 3X,'*****',8X,'**',9X,'*',7X,'*****')
C**** DYNAMIC SECTION
2 CONTINUE
CALL PRINT(TIME,DT,PI,AZ,Z)
CALL DYMOD(TIME,DT,IOD)
CALL ANMOD(TIME,ND)
IF(TIME.GT.ENDT) GO TO 3
TIME=TIME+DT
GO TO 2
3 CONTINUE
C**** END OF SIMULATION
STOP
END

```

```

C**** PRINT SUBROUTINE
SUBROUTINE PRINT(T,DT,PI,AZ,Z)
DIMENSION Z(2),AZ(2)
COMMON/INTEG/JS4,JS,JE,ND
T1=PI*DT
IF(T.EQ.0.0) GO TO 18
XPR=T/T1
IPRI=NINT(XPR)
IF(IPRI.EQ.0) GO TO 19
XPRI=FLOAT(IPRI)
XR=XPRI/XPR
IF(ABS(XR-1.)<.1E-7) GO TO 18
GO TO 19
18 CONTINUE
IF(JS4.NE.0.OR.JS.NE.0) GO TO 19
ERROR=AZ(1)-Z(1)
WRITE(2,1)T,AZ(1),Z(1),ERROR
1 FORMAT(4(F10.7))
19 CONTINUE
RETURN
END

C**** NUMERICAL MODULE
SUBROUTINE DYMOD(TIME,DT,IOD)
COMMON/INTEG/JS4,JS,JE,ND
COMMON/MODEL/Z(2),AZ(2),DZ(2),A,B
IPASS=0
1 CONTINUE
C**** DERIVATIVE SECTION
DZ(1)=Z(2)
DZ(2)=-Z(1)
C**** INTEGRATION SECTION
STP=TIME
DO 2 INTCAL=1,ND
TIME=STP
CALL INTJS(JS4,JS,JE,IOD,IPASS)
CALL SDINT(Z(INTCAL),DZ(INTCAL),TIME,DT,IOD,INTCAL)
2 CONTINUE
C**** UPDATE INTEGRATION PASS NUMBER
IPASS=IPASS+1
C**** CHECK FOR THE END OF THE STEP
CALL INTPAS(IPASS,IOD)
IF(JS.NE.0.OR.JS4.NE.0) GO TO 1
RETURN
END

C**** ANALYTICAL MODULE
SUBROUTINE ANMOD(TIME,ND)
COMMON/MODEL/Z(2),AZ(2),DZ(2),A,B
AZ(1)=SIN(TIME)
RETURN
END

```



```

C**** SUBROUTINE CONTROLLING THE INTEGRATOR PASSES
SUBROUTINE INTJS(JS4,JS,JE,IOD,IPASS)
IF( IOD.EQ.1) RETURN
IF( IOD.EQ.2) JS=IPASS
IF( IOD.EQ.4) JS4=IPASS
RETURN
END

```

```

C**** SUBROUTINE FOR CHECKING THE STEP COMPLETION
SUBROUTINE INTPAS(IPASS,IOD)
COMMON/INTEG/JS4,JS,JE,ND
IF( IOD.EQ.1)
IF( JS.GT.2 ) RETURN
IF( JS4.GT.4) JS=0
IF( IOD.EQ.2.AND.IPASS.GT.2) JS4=0
IF( IOD.EQ.4.AND.IPASS.GT.4) IPASS=0
RETURN
END

```

```

C**** INTEGRATOR
SUBROUTINE SDINT(XX,DX,TD,DTD,IOD,INTCAL)
COMMON/INTEG/JS4,JS,JE,ND
DIMENSION XA(2),DXA(2)
IO=IOD
IF(INTCAL.EQ.1) JN=0
GO TO (6,5,1,1) , IO
6 CONTINUE
GO TO 7

```

```

C*****
5 JS=JS+1
IF(JS.EQ.3) GO TO 20
IF(JS.EQ.2) GO TO 10

```

```

C*****
7 DT=DTD
3 TD=TD+DT
GO TO 10
1 JS4=JS4+1
IF(JS4.EQ.1) TJ0=TD
IF(JS4.EQ.2) TJ1=TD
IF(JS4.EQ.3) TJ2=TD
IF(JS4.EQ.4) TJ3=TD
IF(JS4.EQ.5) GO TO 30
IF(JS4.EQ.1) GO TO 2
IF(JS4.EQ.3) GO TO 4
GO TO 10
2 IF(JS4.EQ.1) H1=DT
DT=DTD/2.
GO TO 3
4 TD=TD+DT
IF(JS4.EQ.3) H3=DT
DT=2.*DT
10 CONTINUE
IF(JS4.EQ.2) H2=DT
IF(JS4.EQ.4) H4=DT

```



```

C**** INTEGRATE

      JN=JN+1
      IF(JN.GT.ND) JN=JN-ND
      GO TO (19,18,13,13), I0
C*****
      19 XX=XX+DX*DT
        TD=TD-DTD
        RETURN
C*****
      18 GO TO (11,12), JS
C*****
      11 DXA(JN)=DX
        XX=XX+DX*DT
        RETURN
C*****
      12 XX=XX+(DX-DXA(JN))*DT/2.0
        RETURN
C*****
      13 GO TO (14,15,16,17), JS4
C*****
      14 XA(JN)=XX
        DXA(JN)=DX
        XX=XX+DX*DT
        IF(INTCAL.NE.ND) TD=TJ0
        IF(INTCAL.NE.ND) DT=H1
        RETURN
C*****
      15 DXA(JN)=DXA(JN)+2.0*DX
        XX=XA(JN)+DX*DT
        IF(INTCAL.NE.ND) TD=TJ1
        IF(INTCAL.NE.ND) DT=H2
        RETURN
C*****
      16 DXA(JN)=DXA(JN)+2.0*DX
        XX=XA(JN)+DT*DX
        IF(INTCAL.NE.ND) TD=TJ2
        IF(INTCAL.NE.ND) DT=H3
        RETURN
C*****
      17 DXA(JN)=(DXA(JN)+DX)/6.0
        XX=XA(JN)+DXA(JN)*DT
        IF(INTCAL.NE.ND) TD=TJ3
        IF(INTCAL.NE.ND) DT=H4
        RETURN
C*****
      20 CONTINUE
        TD=TD-DTD
        RETURN
C*****
      30 CONTINUE
        TD=TD-DTD
        RETURN
      END

```

Z=NUMERICAL SOLUTIONS  
 AZ=ANALYTICAL SOLUTIONS  
 IOD=1  
 DT=.01  
 PI=10.  
 ENDT=.5

TIME	AZ	Z	ERROR
****	**	*	*****
0.0000000	0.0000000	0.0000000	0.0000000
0.1000000	0.0898785	0.0998800	-0.0100015
0.2000000	0.1888589	0.1983615	-0.0100027
0.3000000	0.2859522	0.2959542	-0.0100020
0.4000000	0.3801834	0.3901856	-0.0099972
0.5000000	0.4706259	0.4806109	-0.0099850

IOD=2  
 DT=.01  
 PI=10.  
 ENDT=.5

TIME	AZ	Z	ERROR
****	**	*	*****
0.0000000	0.0000000	0.0000000	0.0000000
0.1000000	0.0898785	0.0998351	-0.0099565
0.2000000	0.1888589	0.1986726	-0.0098137
0.3000000	0.2859522	0.2955250	-0.0095728
0.4000000	0.3801834	0.3894245	-0.0092361
0.5000000	0.4706259	0.4794329	-0.0088070

IOD=4  
 DT=.01  
 PI=10.  
 ENDT=.5

TIME	AZ	Z	ERROR
****	**	*	*****
0.0000000	0.0000000	0.0000000	0.0000000
0.1000000	0.0898785	0.0998334	-0.0099549
0.2000000	0.1888589	0.1986693	-0.0098104
0.3000000	0.2859522	0.2955202	-0.0095680
0.4000000	0.3801834	0.3894183	-0.0092299
0.5000000	0.4706259	0.4794255	-0.0087997

IOD = Integration order      DT = Step length  
 PI = Print interval      ENDT = End time  
 Z = Numerical solution      AZ = Analytical solution

Table B.1 : Results of the simulation of a second order system using the SDINT subroutine

### B.1.1 Listings of the Simulators

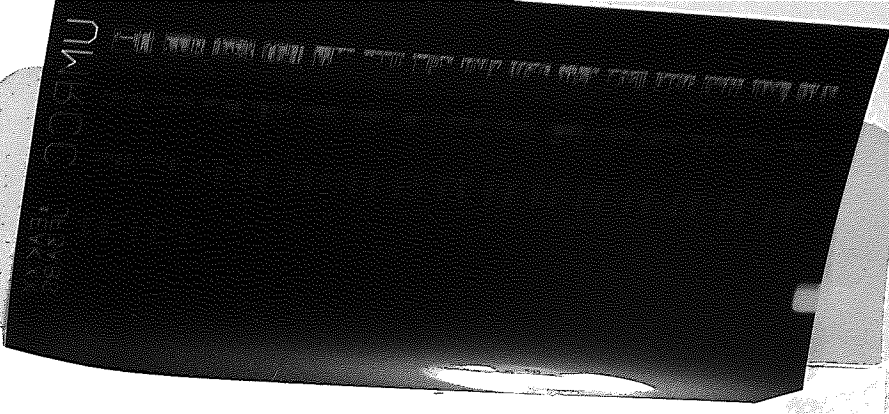
#### The Contents of the Microfiche

Frame A1 : the contents

Frames A1,B1, ... 01: listings of simulator II

A2,B2, ....02 which uses the comprehensive

A3 column model (model II,  
chapter IV)



## B.2 PREDICTION OF PHYSICAL PROPERTIES

### B.2.1 THE CRITICAL TEMPERATURES

The critical temperature  $T_c$  of organic compounds may be accurately estimated to within 1.0 percent by summing the additive contributions of Edjule (1,118). The sum of the contributions  $\Sigma \Delta_T$  is then substituted into

$$T_c = \frac{100 \cdot T_b}{\Sigma \Delta_T}$$

where  $T_b$  and  $T_c$  are the boiling point and critical temperature in  $^{\circ}\text{K}$ . respectively.

### B.2.2 THE CRITICAL PRESSURES

The critical pressure of the organic compounds can also be estimated by summing the additive contributions of Edjule (1,114). Here we have

$$P_c = \frac{10^4 \cdot M}{(\Sigma \Delta_p)^2}$$

where  $M$  = the molecular weight g.mol.

$P_c$  = the critical pressure atm.

$\Sigma \Delta_p$  = the sum of the additive contributions

### B.2.3 THE CRITICAL COMPRESSIBILITY FACTORS

The critical compressibility may be estimated from the equation suggested by Edmister (1,120).

$$Z_c = 0.371 - \frac{0.0343 \log P_c}{(T_c/T_b - 1)}$$

where the symbols and their units are as defined before.

#### B.2.4 THE CRITICAL VOLUMES

The critical volume can be obtained from

$$V_c = \frac{Z_c R T_c}{P_c}$$

#### B.2.5 THE LIQUID DENSITIES

Having estimated the critical properties, the liquid densities can be estimated to an accuracy of 2 percent from the equation suggested by Goyal(1,121).

$$\zeta_l = \frac{P_c M}{T_c} \left( \frac{0.0653}{Z_c^{0.733}} - .09 T_r \right)$$

where  $\zeta_l$  = the liquid density g/cc.

$T_c$  = the critical temperature °K.

$P_c$  = the critical pressure atm.

$T_r$  = the reduced temperature

#### B.2.6 THE LIQUID VISCOSITIES

The liquid viscosities can be estimated from the modified Arrhenius' relation (122)

$$\mu_b = 0.324 \zeta_{lb}^{0.5}$$

where  $\zeta_{lb}$  = the density at boiling point g/cc.

$\mu_{lb}$  = the viscosity at boilint point centipoise

It must be noted that this equation is only applicable at the boiling point.

#### B.2.7 THE DIFFUSIVITY IN LIQUIDS

The theory of diffusion in liquids is less well developed than for gases. Diffusion coefficients in



liquids are typically about for orders of magnitude smaller than in gases. A recommended relation for estimation of diffusivities of non-electrolytes in liquids is due to Wilke and Chang (123) and is as follows:

$$\frac{D_{LV}}{T} = 7.4 * 10^{-8} * \frac{(XM)^{.5}}{(V_b)^{.6}}$$

In thermodynamically non-ideal solutions the effect concentration on  $D_L$  may be estimated by the equation suggested by Wilke (124)

$$\left(\frac{D_{LV}}{T}\right)_1 = \frac{d \ln a_1}{d \ln x_1} \left\{ x_1 \left(\frac{D_{LV}}{T}\right)_2^0 + (1-x_1) \left(\frac{D_{LV}}{T}\right)_1^0 \right\}$$

where

$\left(\frac{D_{LV}}{T}\right)_1$  = Stoke-Einstein group for diffusion of component 1 in 2 at concentration  $x_1$

$\left(\frac{D_{LV}}{T}\right)_1^0$  = Stoke-Einstein group for diffusion of component 1 in 2 at infinite dilution of 1

$\left(\frac{D_{LV}}{T}\right)_2^0$  = Stoke-Einstein group for diffusion of component 2 in 1 at infinite dilution of 2

$x_1$  = mole fraction of 1

$a_1$  = activity of 1

$D_L$  = diffusivity  $\text{cm}^2/\text{sec.}$

$v$  = viscosity centipoise

$X$  = association parameter

The term  $\frac{d \ln a_1}{d \ln x_1}$  may be determined from vapour-liquid equilibrium data and is 1.0 for ideal solutions. For non-ideal solutions, the term approaches 1.0 as  $x_1$  approaches 1.



### B.2.8 THE VAPOUR DENSITIES

The vapour densities or molar volumes may be calculated from the equations

$$V = \frac{ZRT}{P}$$

$$\zeta_v = \frac{1}{V}$$

where the compressibility factor may be obtained from the Nelson-Obert charts (1).

### B.2.9 THE VAPOUR VISCOSITIES

The Bromley and Wilke (125) modification of the theoretical Hirschfelden method (126) for computing the viscosities of low pressure pure vapours is known to give good results. It requires the knowledge of the critical volume of the vapour which can be predicted and is of the form

$$v^o = \frac{33.3 (MT_c)^{.5}}{V_c^{2/3}} \{f(1.33T_r)\}$$

$$\text{and } f(1.33T_r) = 1.058T_r^{0.645} - \frac{0.261}{(1.9T_r)^{0.9 \log(1.9T_r)}}$$

where

$v^o$  = the viscosity micropoise

$T_c$  = the critical temperature  $^{\circ}\text{K.}$

$V_c$  = the critical volume cc./g.mole

$T_r$  = the reduced temperature

### B.2.10 THE DIFFUSIVITY IN VAPOURS

The study of diffusion, along with viscosity and thermal conduction in vapours and gases, is a part of the well-developed kinetic theory of gases. One of the accounts of this theory is that of Hirschfelder, Curtiss and Bird (126), who gave equations based on various assumptions regarding the nature of the interaction between molecules at collision, from which the values of the diffusion coefficient for a binary mixture may be calculated. The most advanced treatment predicts that the diffusion coefficient should vary only slightly with composition, and this is confirmed by experiment.

When experimentally determined diffusivities are not available, several prediction methods based on the kinetic theory are available to provide estimates. When accurate estimates are desired the Wilke and Lee modification (126) of the equation by Hirschfelder, Bird and Spotz (127) is recommended

$$D_G = \frac{BT^{3/2} \sqrt{(1/M_1) + (1/M_2)}}{Pr_{12}^2 I_D}$$

where

$D_G$  = the diffusivity

$T$  = absolute temperature

$M_1, M_2$  = molecular weights of  
components 1 and 2

$r_{12}$  = collision diameter

$$= \frac{(r_0)_1 + (r_0)_2}{2}$$

cm.<sup>2</sup>/sec.

°K.

g.mole

Angstroms

$$r_o = (1.18V_b)^{1/3}$$

$$V_b = \text{molal volume of the liquid cc./g.mol. at normal boiling point}$$

$$I_D = \text{Collision integral for diffusion function } KT/e_{12}$$

$$\frac{e_{12}}{K} = \sqrt{\left(\frac{e_1}{K}\right) \left(\frac{e_2}{K}\right)}$$

$$K = \text{Boltzman constant} = 1.38 \times 10^{-6} \text{ erg/}^\circ\text{K.}$$

$$\frac{e}{K} = 1.15T_b$$

The collision integral can be calculated from

$$I_D = \frac{L}{(T^*)^M} + \frac{N}{\text{Exp}(RT^*)} + \frac{Z}{\text{Exp}(WT^*)}$$

where

$$L = 1.16415; M = .14874 \quad N = .52487$$

$$R = .77320; Z = 2.16178; W = 2.43787$$

$$T^* = \frac{KT}{e}$$

$$\text{Also } B = (1.0 - 2.46 \sqrt{(1/M_1 + 1/M_2)}) \times 10^{-4}$$

For multicomponent systems, the diffusivity may be a strong function of composition and is different for each component (124).

#### B.2.11 THE DENSITIES OF THE LIQUID AND VAPOUR MIXTURES

The fictitious or average density for binary liquid mixtures is defined as follows:

$$\zeta_{m\ell} = (x\zeta_\ell)_1 + (x\zeta_\ell)_2$$

similarly for the vapour phase

$$\zeta_{mv} = (y\zeta_v)_1 + (y\zeta_v)_2$$

where  $x$  and  $y$  are the mole fractions in liquid and vapour phases.

### B.2.12 THE VISCOSITIES OF THE LIQUID AND VAPOUR MIXTURES

The viscosity of a vapour mixture may be calculated from

$$\nu_{mv} = \frac{\sum y_i \nu_i (M_i)^{0.5}}{\sum y_i (M_i)^{0.5}}$$

where

$\nu_{mv}$  = the viscosity of the vapour mixture

$\nu_i$  = the component viscosities

$M_i$  = the component molecular weights

The viscosity of a binary liquid mixture can be calculated from

$$\nu_{ml} = ((x\nu)_1^{1/3} + (x\nu)_2^{1/3})^3$$

where  $x$  refers to the mole fractions and subscripts 1 and 2 refer to the components.

### B.2.13 THE SPECIFIC HEAT CAPACITIES

The low-pressure heat capacities of pure organic compounds may be estimated with good accuracy with Dobratz's equation (114,130)

$$C_p^0 = 4R + n_r' \frac{R}{2} + \sum q_i C_{vi} + \frac{3n-6-n_r'-\sum q_{iv}}{\sum q_i} \sum q_i C_{\delta i}$$

in conjunction with the tables given by Reid and Sherwood (1,114,130) which give the Meghreblian's recommendations (132) for the characteristic stretching and bending vibrational wave numbers ( $\nu$  and  $\delta$ ), along

with the corresponding constants of the heat-capacity equation

$$C_p^0 = A + BT + CT^2$$

as obtained from the analysis of Crawford and Parr (133).  
In these equations

$C_p$  = the specific heat capacity cal./(g.mole) ( $^{\circ}$ K.)

$R$  = the universal gas constant cal./(g.mole) ( $^{\circ}$ K.)  
= 1.987

$n$  = the total number of atoms in the molecule

$q_i$  = the number of atoms of the  $i$ th type

$\Sigma q_i$  = the total number of bonds in the molecule

$C_{vi}$  and  $C_{\delta i}$  = the Einstein functions for bonds of the  
ith type

$n_r$  = the number of single bonds about which  
internal rotation of groups can take  
place

A P P E N D I X C



## C.1 THE PROPERTIES OF THE LIQUID SYSTEM

### C.1.1 VAPOUR-LIQUID EQUILIBRIUM DATA

The vapour-liquid equilibrium of the binary liquid system consisting of Trichloroethylene and Tetrachloroethylene at atmospheric pressure has been investigated by Bachman (135). The activity coefficients needed for the calculation of Van-Larr constants are also given in the aforementioned article.

### C.1.2 VAPOUR-PRESSURE-TEMPERATURE DATA

The vapour-pressure-temperature data needed for the calculation of Antoine equation constants are found in The International-Critical-Tables (138).

### C.1.3 MISCELLANEOUS PROPERTIES AT 20°C

Property	Trichloroethylene	Tetrachloroethylene	Units
$\zeta$	1.4642	1.6475	g./cc.
$\bar{C}_p$	0.9040	0.8830	J./g.°C
$\lambda$	239.60	209.50	J./g.

where:  $\zeta$  = density

$\bar{C}_p$  = specific heat capacity

$\lambda$  = latent heat of vapourization

The data given in the table above are from the International Critical Tables (138).



### C.1.3 THE CRITICAL PROPERTIES

The critical properties of the two components of the liquid system are shown in the table below.

Property	Trichloroethylene	Tetrachloroethylene	Units
$P_C$	54.448	40.72	atm.(abs.)
$T_C$	560.94	597.80	$^{\circ}K.$
$V_C$	$2.68 \times 10^{-4}$	$3.44 \times 10^{-4}$	$m^3/mol.$
$Z_C$	0.265	0.286	-

where:  $P_C$  = critical pressure

$T_C$  = critical temperature

$Z_C$  = critical compressibility

$V_C$  = critical volume

### C.1.4 MISCELLANEOUS PROPERTIES AT BOILING POINTS

Property	Trichloroethylene	Tetrachloroethylene	Units
$\zeta_{lb}$	10089.734	8686.75	$mol./m^3$
$V_b$	$2.95 \times 10^{-2}$	$3.21 \times 10^{-2}$	$m^3/mol.$

where:  $\zeta_{lb}$  = liquid density at boiling point

$V_b$  = molar volume at boiling point

## C.2 THE ESTIMATION OF THE HEAT LOSSES

### C.2.1 HEAT LOSSES FROM THE PIPE SECTION WHICH ENABLES GRAVITY FLOW

The heat losses from the pipe section, added to the top of the column in order to enable gravity flow, will cause the condensation of the overhead vapour passing through the pipe which, in turn, appears in the form of additional reflux and thus affects the operation of the column.

The following assumptions have to be made to render the estimation of the heat thus lost to the atmosphere possible:

- (i) the resistance to heat transfer is mainly due to the fibre glass lagging
- (ii) the glass is at the same temperature as the overhead vapour at steady-state

#### Typical Estimation Procedure for Steady-State

##### Experiment No.5

The thermal conductivity of the lagging =  $0.27 \text{ B.T.U./hr.}^{\circ}\text{F.ft}^2\text{/in.}$

Total heat transfer area	= 2.57	$\text{ft.}^2$
Atmospheric temperature	= 66.2	$^{\circ}\text{F.}$
Glass Temperature	= 188.6	$^{\circ}\text{F.}$
The thickness of the lagging	= 1	inch

$$\begin{aligned}\therefore Q &= \frac{KA\delta T}{x} = \frac{(0.27)(2.5687)(188.6-66.2)}{1} \\ &= 84.9 \quad \text{B.T.U./hr.} \\ &= 89.6 \quad \text{kJ./hr.}\end{aligned}$$

Therefore the measured reflux rate must be corrected as follows:

Measured reflux rate = 118.5 cc./min.

$$= 61.2 \quad \text{g.mol./hr.}$$

$$\text{Additional reflux} = \frac{89.568}{31.5074} = 2.8 \quad \text{g.mol./hr.}$$

$$\therefore \text{Total reflux} = 82.0 \quad \text{g.mol./hr.}$$

### C.2.2 HEAT LOSSES FROM THE COLUMN

The heat losses from the column will simply appear as the extra heat which has to be provided by the reboiler in addition to the heat needed to vapourize one mole of the liquid inside the reboiler. The assumptions made are the same as the ones made in order to estimate the amount of heat losses from the gravity flow pipe section. Average temperatures are assumed in the enriching and stripping sections.

### Typical Estimation Procedure for Steady-State

#### Experiment No.5

(a) The Enriching Section

$$\text{Average Vapour Temperature} = 200.5 \quad ^\circ\text{F.}$$

$$\text{Area} = 1.68 \quad \text{ft.}^2$$

$$\text{Ambient Temperature} = 66.2 \quad ^\circ\text{F.}$$

$$\begin{aligned}\therefore Q_e &= \frac{K A_e \delta T_e}{x} \\ &= \frac{(0.27)(1.67836)(200.468-66.2)}{1} = 60 \text{ B.T.U./hr.} \\ &= 64.2 \text{ kJ./hr.}\end{aligned}$$

(b) The Stripping Section

$$\begin{aligned}\text{Average Temperature} &= 225.8 \text{ } ^\circ\text{F.} \\ \text{Area} &= 1.4 \text{ ft.}^2 \\ \text{Ambient Temperature} &= 66.2 \text{ } ^\circ\text{F.}\end{aligned}$$

$$\begin{aligned}\therefore Q_s &= \frac{k A_s \delta T_s}{x} \\ &= \frac{(0.27)(1.40216)(225.804-66.2)}{1} \approx 61.2 \text{ B.T.U./hr.} \\ &\approx 64.6 \text{ kJ./hr.}\end{aligned}$$

(c) The Heat Losses from the Reboiler

Assuming that the reboiler is spherical the estimated uncovered area is approximately 0.089 square metres. Now

$$\begin{aligned}Q_b &= UA \delta T_b \\ &= 30 \times 0.0894 \times (114-19) \times 4.186 \approx 1066 \text{ kJ./hr.}\end{aligned}$$

Therefore an estimate of the total heat losses can be obtained by summing the individual estimates of heat losses calculated in sections (a), (b) and (c) as

$$\delta Q_{\text{lost}} = 64.2 + 64.6 + 1066 \approx 1195 \text{ kJ./hr.}$$

$$\text{Actual heat input } Q_{\text{actual}} \approx 4805 \text{ kJ./hr.}$$

$$\therefore Q_{\text{adiabatic}} \approx 3610 \text{ kJ./hr.}$$

A P P E N D I X D



## CONTENTS

- D.1 Description of the latest version of the HADIOS Executive and its modifications for this research
- D.2 The listing of the HADIOS Executive in the Assembler symbolic language
- D.3 The listing of subroutine 5; modification No.1
- D.4 The listing of the patch added to the analogue inputs : modification No.2

This version of the HADIOS Executive Package provides facilities for accessing all the available HADIOS devices from a BASIC program. It therefore supersedes all previous versions.

Devices Available

(1) Analogue inputs

48 analogue channels (numbered 0-47) are multiplexed through a common ADC which has an input range of 0-5V. The converted digital input to the computer is in the range 0-1023.

(2) Counter inputs

Three counters are available. Each counter has a range 0-255 and after 255 pulses have been counted the counter returns to zero and resumes counting. The counters can also be programmed to interrupt on reaching a count of 127. In both cases the counters can be preset to an initial (positive) value  $\leq 255$  after each scan or counter interrupt.

(3) Digital inputs

Two digital inputs are available. Each has 16 parallel input lines whose values (0 or 1) can be read into the computer.

(4) Digital outputs

Two digital outputs are available. Each has 16 parallel output lines whose values (0 or 1) can be sent out by the computer. The values output remain constant until the next 16 bit word is



sent out. Four forms of output are available  
(see below).

### Programming Details

All HADIOS input/output is done when subroutine 1  
(see below) is first called and thereafter at the end  
of a time interval selected by the user.

The user communicates with HADIOS by CALL's from  
his BASIC program as follows:

CALL (1, A(0), B(0))

Subroutine 1 is the basic scanning routine. Arrays  
A (dimensioned 13) and B (dimensioned 120) contain the  
users parameters and variables.

A(0)            Scanning interval (sec)

A(1)            Devices required

=1	Analogue inputs
=2	Counter 1
=4	Counter 2
=8	Counter 3
=16	Digital input A
=32	Digital input B
=64	Digital output A
=128	Digital output B

The required set of devices is selected by setting  
A(1) equal to the sum of the appropriate values above.

- A(2) Number of scans required (including the initial scan at time zero).
- A(3) First analogue channel.
- A(4) Last analogue channel.
- A(5) Number of samples of each analogue channel per scan (ensemble number).
- A(6) Counter 1 scan type.  
=0 no counter interrupt.  
=1 enable counter interrupt.
- A(7) Counter 1 preset value.
- A(8) Counter 2 scan type.
- A(9) Counter 2 preset value.
- A(10) Counter 3 scan type.
- A(11) Counter 3 preset value.
- A(12) Digital output A mode.  
=0 from 16 element array at BASIC level  
(see below).  
=1 from subroutine 3 or 4 (see below).  
=2 from user supplied subroutine (see below).
- A(13) Digital output B mode.
- B(0) - B(47) Analogue input channel readings  
(each averaged over A(5) samples).
- B(48) Counter 1 interrupt time (sec).
- B(49) Counter 1 contents at scanning time.
- B(50) Number of interrupts by counter 1 during last scanning interval.
- B(51) Counter 2 interrupt time (sec).
- B(52) Counter 2 contents at scanning time.

B(53) Number of interrupts by counter 2 during last scanning interval.

B(54) Counter 3 interrupt time (sec).

B(55) Number of interrupts by counter 3 during last scanning interval.

B(57) - B(72) Values (0 or 1) read on bits 1-16 of digital input A.

B(73) - B(88) Values (0 or 1) read on bits 1-16 of digital input B

B(89) - B(104) Values (0 or 1) output on bits 1-16 of digital output A (when A(12)=0).

B(105) - B(120) Values (0 or 1) output on bits 1-16 of digital output B (when A(13)=0).

#### CALL (2)

This CALL causes the program to wait for the next clock interrupt (scan time) if all scans requested (A(2)) have not been done. Otherwise the BASIC program continues from after the CALL (2).

On a clock interrupt, a scan is performed and the BASIC program continues from after the previous CALL (1, ...) - the inter-scan processing section of the program.

CALL (2) disables clock and counter(s) interrupt when all scans requested have been done.

#### CALL (3, D, N, X)

This subroutine provides for a special form of digital output to send out an analogue signal by means of extra hardware when A(12) = 1 or A(13) = 1.

D =0 digital output A.  
 =1 digital output B.  
 N = analogue output channel (1-15).  
 X = digital equivalent of analogue output.

For  $0 < X < 32767$ , the analogue output will be 0-10v.

#### CALL (4, D, I, C)

This subroutine controls the format of the digital output when  $A(12) = 1$  or  $A(13) = 1$  as follows:

D =0 digital output A.  
 =1 digital output B.  
 I <0 reset all 16 bits to zero.  
 >0 set bits  $15-2*I$  and  $16-2*I$  to value of C leaving other bits unchanged,  $0 < I < 7$ .  
 C = 0, 1, 2 or 3 only.

This subroutine has been provided to control up to 8 valve drives. Normally, therefore, only 3 values of C will be used (say 0, 1 and 2).

#### Sense Switch Usage

S.S. 1 - Normal use for terminating a BASIC program (not recommended).  
 S.S. 2 - As for S.S. 1 but interrupts are also disabled (see below).  
 S.S. 3 - INPUT statement reads data from tape.  
 S.S. 4 - PRINT statement writes data to tape.

#### Error Messages

Error Message Format : ERROR XY LINE NNN, where XY is one of the following:



1. TF - the clock interrupt frequency is too small and so BASIC code was still being executed when a clock interrupt took place. This would obviously lead to a backlog of processing at the BASIC level if it were allowed to go unchecked and so execution is terminated.
2. NR - an unidentifiable interrupt has occurred and execution is terminated.
3. NC - the Hados controller has interrupted the central processor but the interrupting device was not a counter. Execution is terminated.
4. UI - the execution of the program has been terminated by user interference. This is caused by setting sense switch 2. When interrupt is occurring it is preferable to terminate execution in this way rather than by setting sense switch 1 as the setting of sense switch 2 causes all interrupts to be disabled.
5. RI - a real to integer conversion error has occurred in the HADIOS EXECUTIVE i.e. conversion of a real number outside the range -32768 to +32767 was attempted.
6. SE - user supplied subroutine has been called (A(12) or A(13) = 2) but is not loaded.

#### User Supplied Subroutine

The user may also supply his own DAP-16 routine to control a digital output device.

The present package contains a dummy version of this routine (called MYSR) which does not cause any

output. The user supplied subroutine is called by setting A(12) or A(13) = 2. The starting address of the routine should be patched into location '37603 (SPSR).

Note that only one of subroutine 3, 4 or the special routine may be used for digital output A or B in the same program and at present only one user supplied routine may be added to the package.

In all cases the requested digital output will be performed at the next clock interrupt.

#### Further Subroutines

Additional routines may be added to the HADIOS Executive (e.g. for graphics etc). Such routines must be loaded in sector 35 and below with the base of COMMON (if any) at '35777. There can be 6 routines called from BASIC (numbered 5 to 10). The starting addresses of the routines should be patched into locations '522 onwards and '230 (DAC IBUF) should be patched into '36221 onwards for as many subroutines as can be called from BASIC (i.e. '36221 for subroutine 5 etc).

The address of the first location below the subroutines should be patched into location '7367.

Note that only locations '733 - '777 are available for BASE in sector 0. If more BASE is required it must be located elsewhere (by setting the B register at load time etc).

#### Counter Calculations

The counter rate may be calculated either from the counter interrupt time or from the number of interrupts

over a scan interval and the counter contents at the next scan. Thus for counter 1

$$\text{Rate} = (127 - A(7))/B(48)$$

$$\text{or Rate} = ((127 - A(7)) * B(50) + B(49)) / A(0)$$

with similar expressions for counters 2 and 3.

The latter form is more accurate if the rate is constant over the period A(0) but the former gives an 'instantaneous' rate.

Note that the values of B(48), B(51) and B(54) have no significance at time zero (first scan).

Executive Package Revision 02 (1978)

Modification No. 01

Use of subroutine 3 allows only one analogue channel per digital output to be changed at a clock interrupt.

It may be that more than one analogue output is to be changed and that the changes need not wait until the next clock interrupt.

Subroutine 5 has been added to implement this facility. In CALL (5, D, N, X) the arguments have the same meaning as in subroutine 3 but the value X is output immediately on channel N of device D.

Note that if digital output is only through subroutine 5, A(1) should not be set for the digital output device.

Digital output at a clock interrupt may still be carried out by all modes previously described.



Subroutine 5 has been loaded from '35734. Further subroutines (6-10) may be added below this address.

Executive Package Revision 02 (1979)

Modification No. 02

This patch enables the scanning interval to be divided into as many subintervals of 20  $\mu$ sec duration as possible - a value of A(5) is calculated. The samples of the analogue input channels are thus spaced out over the entire scanning interval as opposed to being taken instantaneously according to a prespecified value of A(5).

The sole advantage of this modification is that it enables the noise (if any) to be smoothed out more effectively during the scanning of the analogue input channels.

Note that A(5) no longer needs to be specified. Also CTS, location '37776 contains a big negative number which can be keyed in at load time. The bigger the number the smaller the number of samples. The present value is -33.



```

0058
0059
0060
0061 00017 0 10 00073 LINK LNKA,1,LNKA
0062 00020 000000 BSZ 5
0063 00025 000001 OCT 1
0064 00026 0 000020 DAC LNKA+1
0065 00027 0 000000 LNKA DAC **
0066 00030 0 35 00026 LDX *-2
0067 00031 0 01 00120 JMP CTR
0068
0069
0070
0071
0072
0073 00032 0 10 00073 LINK LNKB,10,LNKB
0074 00033 000000 BSZ 5
0075 00040 000010 OCT 10
0076 00041 0 000033 DAC LNKB+1
0077 00042 0 000000 LNKB DAC **
0078 00043 0 35 00041 LDX *-2
0079 00044 0 01 00120 JMP CTR
0080
0081
0082 00045 0 10 00073 LINK LNKC,10,LNKC
0083 00046 000000 BSZ 5
0084 00053 000010 OCT 10
0085 00054 0 000046 DAC LNKC+1
0086 00055 0 000000 LNKC DAC **
0087 00056 0 35 00054 LDX *-2
0088 00057 0 01 00120 JMP CTR
0089
0090
0091 00060 0 10 00073 LINK LNKD,10,LNKD
0092 00061 000000 BSZ 5
0093 00066 000010 OCT 10
0094 00067 0 000071 DAC LNKD+1
0095 00070 0 000000 LNKD DAC **
0096 00071 0 35 00067 LDX *-2
0097 00072 0 01 00120 JMP CTR
0098
0099
0100
0101 00073 0 000000 CTR DAC **
0102 00074 -0 15 00073 STX* CTR
0103 00075 0 35 00073 LDX CTR
0104 00076 1 13 00001 IMA 1,1
0105 00077 000043 INK
0106 00100 000005 SGL
0107 00101 1 04 00002 STA 2,1
0108 00102 0 02 00000 LDA SKST
0109 00103 1 04 00004 STA 4,1
0110 00104 1 02 00005 LDA 5,1
0111 00105 140401 CMA
0112 00106 0 03 00162 ANA MASK
0113 00107 0 04 00162 STA MASK
0114 00110 74 00200 SMK 120

```

R115	00111	1 02 00007	LDA	7,1
R116	00112	0 04 00117	STA	CIHA
R117	00113	000201	IAB	
R118	00114	1 04 00003	STA	3,1
R119	00115	000011	LXA	
R120	00116	-0 01 00117	JMP*	CIHA
R121	00117	000000	CIHA BSZ	1
R122			*	
R123			* COMMON INTERRUPT RETURN	
R124			*	
R125	00120	1 02 00003	CIR LDA	3,1
R126	00121	000201	IAB	
R127	00122	1 02 00005	LDA	5,1
R128	00123	140401	CMA	
R129	00124	001001	INH	
R130	00125	0 03 00162	ANA	MASK
R131	00126	1 05 00005	EKA	5,1
R132	00127	0 04 00162	STA	MASK
R133	00130	74 0020	SMK	120
R134	00131	1 02 00004	LDA	4,1
R135	00132	0 04 00160	STA	CIKA
R136	00133	1 02 00000	LDA	0,1
R137	00134	0 04 00161	STA	CIRK
R138	00135	1 02 00002	LDA	2,1
R139	00136	171020	OTK	
R140	00137	1 13 00001	IMA	1,1
R141	00140	0 35 00161	LIX	CIRK
R142	00141	000401	ENR	
R143	00142	-0 01 00160	JMP*	CIKA
R144			*	
R145			* COMMON INTERRUPT INITIATOR	
R146			*	
R147	00143	0 000000	CII DAC	**
R148	00144	-0 35 00143	LIX*	CII
R149	00145	0 12 00143	IRS	CII
R150	00146	1 02 00000	LDA	0,1
R151	00147	140401	CMA	
R152	00150	0 03 00162	ANA	MASK
R153	00151	1 05 00000	EKA	0,1
R154	00152	74 0020	SMK	120
R155	00153	0 04 00162	STA	MASK
R156	00154	-0 02 00143	LDA*	CII
R157	00155	0 12 00143	IRS	CII
R158	00156	1 04 00002	STA	2,1
R159	00157	-0 01 00143	JMP*	CII
R160	00160	000000	CIKA BSZ	1
R161	00161	000000	CIRK BSZ	1
R162	00162	000000	MASK BSZ	1
R163	00163	005243	ERR OCT	5243
R164			*	
R165			* DISPATCHER	
R166			*	
R167	00164	0 35 00674	DISP LIX	=-5
R168	00165	1 02 00211	LDA	GOAD+5,1
R169	00166	100040	SZF	
R170	00167	0 01 00177	JMP	DISC
R171	00170	100010	SK2	

```

0172 00171 0 01 00175 JMP STOP
0173 00172 0 12 00000 IKS 0
0174 00173 0 01 00165 JMP DISF+1
0175 00174 0 01 00164 JMP DISF
0176 00175 0 10 00106 STOP JST EROL
0177 00176 152711 BCI 1,01
0178 00177 0 04 00203 DISO STA DISS
0179 00200 140040 CRA
0180 00201 1 04 00211 STA GOAD+5,1
0181 00202 -0 01 00203 JMP* DISS
0182 00203 000000 DISS BSZ 1
0183 00204 000000 GOAD BSZ 5
0184
0185
0186
0187 00211 0 02 00230 CALL LDA THUF
0188 00212 0 07 00515 SUB CJST
0189 00213 0 04 00000 STA 0
0190 00214 -1 01 00214 JMP* TABL-1,1
0191 00215 0 000227 TABL DAC SUB1
0192 00216 0 000372 LAC SUB2
0193 00217 0 000451 DAC SUB3
0194 00220 0 000516 DAC SUB4
0195 00221 0 004064 DAC SS
0196 00222 0 004064 DAC SS
0197 00223 0 004064 DAC SS
0198 00224 0 004064 DAC SS
0199 00225 0 004064 DAC SS
0200 00226 0 004064 DAC SS
0201
0202
0203
0204
0205
0206 00227
0207 00227 0 02 00034 LDA SIF
0208 00230 0 04 00442 STA SIF1
0209 00231 0 02 00037 LDA SHF
0210 00232 0 04 00443 STA SHF1
0211 00233 0 02 00437 LDA NEXT
0212 00234 0 04 00236 STA **2
0213 00235 0 01 00237 JMP **2
0214 00236 0 000000 DAC **
0215 00237 -0 10 00441 JST* FA1
0216 00240 000002 DEC 2
0217 00241 000000 PARS BSZ 2
0218 00243 -0 10 00653 JST* L22
0219 00244 -0 000241 LAC* PARS
0220 00245 -0 10 00674 JST* M22
0221 00246 0 000447 DAC F50
0222 00247 -0 10 00676 JST* C21
0223 00250 0 01 00370 JMP ENI
0224 00251 140407 TCA
0225 00252 0 04 00440 STA CINT
0226 00253 0 02 00241 LDA PARS
0227 00254 0 06 00673 ADD =10
0228 00255 0 04 01452 STA REF+3

```

USER INTERFERED

\* BASIC ENTRY POINT

\* SUBROUTINE 1

```

*
* SAVE SIF1, SHF1
* SUB1 BSS 0

```

0229 00256	0 12 00241	IRS	PARS
0230 00257	0 12 00241	IRS	PARS
0231 00260	0 35 00672	LDX	=-13
0232 00261	0 15 00446	STX	K1
0233 00262	-0 10 00653	JST*	L22
0234 00263	-0 000241	DAC*	PARS
0235 00264	-0 10 00676	JST*	C21
0236 00265	0 01 00370	JMP	ERI
0237 00266	0 35 00446	LDX	K1
0238 00267	1 04 00435	STA	CTRS+13,1
0239 00270	0 12 00241	IRS	PARS
0240 00271	0 12 00241	IRS	PARS
0241 00272	0 12 00000	IRS	0
0242 00273	0 01 00261	JMP	*-10
0243 00274	0 02 00435	LDA	DACS
0244 00275	0 04 00063	STA	'F3
0245 00276	0 02 00436	LDA	FRST
0246 00277	0 04 00061	STA	'F1
0247 00300	0 35 00674	LDX	=-5
0248 00301	140040	CHA	
0249 00302	0 04 00515	STA	IFLG
0250 00303	0 04 00162	STA	MASK
0251 00304	0 04 01601	STA	SCAN
0252 00305	1 04 00211	STA	GOAL+5,1
0253 00306	0 12 00000	IRS	0
0254 00307	0 01 00305	JMP	*-2
0255			
0256			
0257 00310	0 10 00143	INTI	LNRA, ACLK, CLK
0258 00311	0 000025	JST	C11
0259 00312	0 001000	DAC	LNRA-2
0260 00313	14 0020	DAC	ACLK
0261		OCP	CLK
0262			
0263 00314	0 02 00420	DVCE	=2, A1
0264 00315	0 03 00671	LDA	CTRS
0265 00316	101040	ANA	=2
0266 00317	0 01 00332	SNZ	
0267		JMP	A1
0268			
0269 00320	0 02 00426	SET	6, SET1
0270 00321	74 0570	LDA	CTRS+7
0271 00322	0 01 00321	OTA	SET1
0272		JMP	*-1
0273			
0274 00323	0 02 00425	CTII	5, A1, LNRA, ICT1, CTR1
0275 00324	101040	LDA	CTRS+5
0276 00325	0 01 00332	SNZ	
0277 00326	0 10 00143	JMP	A1
0278 00327	0 000040	JST	C11
0279 00330	0 000603	DAC	LNRA-2
0280 00331	14 0470	DAC	ICT1
0281		OCP	CTR1
0282			
0283 00332		DVCE	=4, A2
0284 00332		BSS	0
0285 00333	0 02 00420	LDA	CTRS
	0 03 00670	ANA	=0



0286	00334	101040	SNZ	
0287	00335	0 01 00350	JMP	A2
0288			*	
0289			*	SET 8, SET2
0290	00336	0 02 00400	LDA	CTRS+8
0291	00337	74 0770	OTA	SET2
0292	00340	0 01 00337	JMP	*-1
0293			*	
0294			*	CTII 7, A2, LNR0, ICT2, CTR2
0295	00341	0 02 00427	LDA	CTRS+7
0296	00342	101040	SNZ	
0297	00343	0 01 00350	JMP	A2
0298	00344	0 10 00143	JST	CII
0299	00345	0 000053	DAC	LNR0-2
0300	00346	0 000024	DAC	ICT2
0301	00347	14 0670	OCF	CTR2
0302			*	
0303			*	DVCF =8, INT
0304	00350		A2	RSS 0
0305	00350	0 02 00420	LDA	CTRS
0306	00351	0 03 00667	ANA	=8
0307	00352	101040	SNZ	
0308	00353	0 01 00366	JMP	INT
0309			*	
0310			*	SET 10, SET3
0311	00354	0 02 00432	LDA	CTRS+10
0312	00355	74 0370	OTA	SET3
0313	00356	0 01 00355	JMP	*-1
0314			*	
0315			*	CTII 9, INT, LNR0, ICT3, CTR3
0316	00357	0 02 00431	LDA	CTRS+9
0317	00360	101040	SNZ	
0318	00361	0 01 00366	JMP	INT
0319	00362	0 10 00143	JST	CII
0320	00363	0 000066	DAC	LNR0-2
0321	00364	0 000045	DAC	ICT3
0322	00365	14 0270	OCF	CTR3
0323	00366	000401	INT	ENF
0324	00367	0 01 00164	JMP	DISP
0325	00370	0 10 01606	FRI	FRCL
0326	00371	151311	BCI	1, RI
0327			*	
0328			*	SUBROUTINE 2
0329			*	
0330	00372	001001	SUB2	INH
0331			*	
0332			*	SAVE SIF2, SHP2
0333	00373	0 02 00034	LDA	SIF
0334	00374	0 04 00444	STA	SIF2
0335	00375	0 02 00037	LDA	SHP
0336	00376	0 04 00445	STA	SHP2
0337	00377	140040	CRA	
0338	00400	0 04 00515	STA	IFLG
0339	00401	0 02 01601	LDA	SCAN
0340	00402	0 07 00421	SUB	CTRS+1
0341	00403	101400	SMT	
0342	00404	0 01 00407	JMP	*+3

REAL TO INTEGER



0343 00405	000401	ENB	
0344 00406	0 01 00164	JMP	DISH
0345 00407	14 0220	OCP	SCLK
0346 00410	14 0570	OCP	SE11
0347 00411	14 0770	OCP	SE12
0348 00412	14 0370	OCP	SE13
0349			
0350		*	
0351 00413	0 02 00444	* REST	SIP2, SHP2
0352 00414	0 04 00034	LDA	SIP2
0353 00415	0 02 00445	STA	SIP
0354 00416	0 04 00037	LDA	SHP2
0355 00417	-0 01 01600	STA	SHP
0356 00420	000000	JMP*	CLFF
0357 00435	0 000000	CTRS BSZ	13
0358 00436	177777	DACS DAC	SKS1
0359 00437	0 000231	FRST DEC	-1
0360 00440	000000	NEXT DAC	IRUF+1
0361 00441	0 000000	CIN1 BSZ	1
0362 00442	000000	FAT XAC	FSA1
0363 00443	000000	SIP1 BSZ	1
0364 00444	000000	SHP1 BSZ	1
0365 00445	000000	SIP2 BSZ	1
0366 00446	000000	SHP2 BSZ	1
0367 00447	041544	K1 BSZ	1
00450	000000	F50 DEC	50.
0368			
0369		*	
0370		* SUBROUTINE 3	
0371 00451	0 12 00515	* SUB3 IRS	IFLG
0372 00452	0 02 00437	LDA	NEXT
0373 00453	0 04 00455	STA	**2
0374 00454	0 01 00456	JMP	**2
0375 00455	0 000000	DAC	**
0376 00456	-0 10 00441	JST*	FAT
0377 00457	000003	DEC	3
0378 00460	000000	D3 BSZ	1
0379 00461	000000	N BSZ	1
0380 00462	000000	X BSZ	1
0381 00463	-0 02 00460	LDA*	D3
0382 00464	100040	SZ F	
0383 00465	0 01 00470	JMP	**3
0384 00466	140040	CRA	
0385 00467	0 01 00471	JMP	**2
0386 00470	140402	OCT	140402
0387 00471	0 06 00512	ADD	ADWD
0388 00472	0 04 00514	STA	CH3+1
0389 00473	-0 10 00653	JST*	L22
0390 00474	-0 000461	DAC*	N
0391 00475	-0 10 00676	JST*	C21
0392 00476	0 01 00370	JMP	ERI
0393 00477	0 04 00513	STA	CH3
0394 00500	-0 10 00653	JST*	L22
0395 00501	-0 000462	DAC*	X
0396 00502	-0 10 00676	JST*	C21
0397 00503	0 01 00370	JMP	ERI
0398 00504	0415 77	ALS	1

LBI

0399	00505	000201	IAB	
0400	00506	0 02 00513	LDA	CH3
0401	00507	0410 64	LLL	12
0402	00510	-0 04 00514	STA*	CH3+1
0403	00511	-0 01 01600	JMP*	CL06
0404	00512	0 001472	ADWD DAC	WRD1
0405	00513	000000	CH3 BSZ	2
0406	00515	000000	IFLG BSZ	1
0407			*	
0408			* SUBROUTINE 4	
0409			*	
0410	00516	0 12 00515	SUB4 IKS	IFLG
0411	00517	0 02 00437	LDA	NEXT
0412	00520	0 04 00522	STA	++2
0413	00521	0 01 00523	JMP	++2
0414	00522	0 000000	DAC	**
0415	00523	-0 10 00441	JST*	FAT
0416	00524	000003	DFC	3
0417	00525	000000	D4 BSZ	1
0418	00526	000000	I4 BSZ	1
0419	00527	000000	C BSZ	1
0420	00530	-0 02 00525	LDA*	D4
0421	00531	100040	SZE	
0422	00532	0 01 00535	JMP	++3
0423	00533	140040	CRA	
0424	00534	0 01 00536	JMP	++2
0425	00535	140402	OCT	140402 LDI
0426	00536	0 06 00512	ADD	ADWD
0427	00537	0 04 00600	STA	CH4+1
0428	00540	-0 02 00526	LDA*	I4
0429	00541	101400	SMI	
0430	00542	0 01 00546	JMP	++4
0431	00543	140040	CRA	
0432	00544	-0 04 00600	STA*	CH4+1
0433	00545	-0 01 01600	JMP*	CL06
0434	00546	-0 10 00653	JST*	L22
0435	00547	-0 000526	DAC*	I4
0436	00550	-0 10 00676	JST*	C21
0437	00551	0 01 00370	JMP	FRI
0438	00552	0 04 00602	STA	I14
0439	00553	-0 10 00653	JST*	L22
0440	00554	-0 000527	DAC*	C
0441	00555	-0 10 00676	JST*	C21
0442	00556	0 01 00370	JMP	FRI
0443	00557	000201	IAB	
0444	00560	0 02 00602	LDA	I14
0445	00561	101040	SNZ	
0446	00562	0 01 00570	JMP	++6
0447	00563	0 07 00666	SUB	=1
0448	00564	000201	IAB	
0449	00565	0415 76	ALS	2
0450	00566	000201	IAB	
0451	00567	0 01 00561	JMP	+-6
0452	00570	000201	IAB	
0453	00571	0 04 00601	STA	CH4+2
0454	00572	1401401	CMA	
0455	00573	-0 03 00600	ANA*	CH4+1

0456	00574	0 05 00601	EKA	CH4+2
0457	00575	-0 04 00600	STA*	CH4+1
0458	00576	-0 01 01600	JMP*	CL06
0459	00577	000000	CH4	BSZ 3
0460	00602	000000	I14	BSZ 1
0461			*	
0462			*	COUNTER INTERRUPTS
0463			*	RESPONSE CODE
0464			*	
0465			*	
0466			*	ICTR ICT1, SET1, 6, CTR1, FLG1, TIM1, ITM1, L
0467	00603	14 0570	ICT1	OCP SET1
0468	00604	0 02 00426	LDA	CTRS+6
0469	00605	74 0570	OTA	SET1
0470	00606	0 01 00605	JMP	*-1
0471	00607	14 0470	OCP	CTR1
0472	00610	0 02 00622	LDA	FLG1
0473	00611	100040	SZF	
0474	00612	0 01 00616	JMP	*+4
0475	00613	0 02 00061	LDA	'61
0476	00614	0 07 01474	SUB	TIM1
0477	00615	0 04 00623	STA	ITM1
0478	00616	0 12 00622	IRS	FLG1
0479	00617	000401	ENB	
0480	00620	0 10 00042	JST	LNKH
0481	00621	0 01 00603	JMP	ICT1
0482	00622	000000	FLG1	BSZ 1
0483	00623	000000	ITM1	BSZ 1
0484			*	
0485			*	ICTR ICT2, SET2, 8, CTR2, FLG2, TIM2, ITM2, L
0486	00624	14 0770	ICT2	OCP SET2
0487	00625	0 02 00430	LDA	CTRS+8
0488	00626	74 0770	OTA	SET2
0489	00627	0 01 00626	JMP	*-1
0490	00630	14 0670	OCP	CTR2
0491	00631	0 02 00643	LDA	FLG2
0492	00632	100040	SZF	
0493	00633	0 01 00637	JMP	*+4
0494	00634	0 02 00061	LDA	'61
0495	00635	0 07 01475	SUB	TIM2
0496	00636	0 04 00644	STA	ITM2
0497	00637	0 12 00643	IRS	FLG2
0498	00640	000401	ENB	
0499	00641	0 10 00055	JST	LNKC
0500	00642	0 01 00624	JMP	ICT2
0501	00643	000000	FLG2	BSZ 1
0502	00644	000000	ITM2	BSZ 1
0503			*	
0504			*	ICTR ICT3, SET3, 10, CTR3, FLG3, TIM3, ITM3, L
0505	00645	14 0370	ICT3	OCP SET3
0506	00646	0 02 00432	LDA	CTRS+10
0507	00647	74 0370	OTA	SET3
0508	00650	0 01 00647	JMP	*-1
0509	00651	14 0270	OCP	CTR3
0510	00652	0 02 00664	LDA	FLG3
0511	00653	100040	SZF	
0512	00654	0 01 00660	JMP	*+4

0513	00655	0 02 00061	LDA	'61
0514	00656	0 07 01476	SUB	TIM3
0515	00657	0 04 00665	STA	IM3
0516	00660	0 12 00664	IRS	FLG3
0517	00661	000401	ENB	
0518	00662	0 10 00070	JST	LNKD
0519	00663	0 01 00645	JMP	IC13
0520	00664	000000	FLG3	BSZ
0521	00665	000000	IM3	BSZ
0522	00666	000001	FIN	
	00667	000010		
	00670	000004		
	00671	000002		
	00672	177763		
	00673	000012		
	00674	177773		

0523                    000675            BASI EQU    \*

0524                    \*

0525                    \* CLOCK INTERRUPT RESPONSE CODE

0526                    \*

0527			ORG	'1000
0528			SEIB	BAS2
0529	01000	14 0220	ACLK	OCF
0530	01001	0 02 00440	LDA	CIN1
0531	01002	0 04 00061	STA	'61
0532	01003	14 0020	OCF	CLK
0533	01004	000401	ENB	
0534	01005	0 02 00024	LDA	LNKA+5
0535	01006	0 07 01466	SUB	BSIF
0536	01007	100400	SPL	
0537	01010	0 01 01604	JMP	STP
0538	01011	0 02 00515	LDA	IFLG
0539	01012	100040	SZE	
0540	01013	0 01 01604	JMP	STP
0541	01014	0 12 00515	IRS	IFLG

\* COUNTER INPUTS

0542				
0543				
0544				
0545				
0546				
0547	01015	001001	CTRI	=2, A3, CTRI, TIM1, 6, SE11, =48, IIM1, F
0548	01016	0 02 00420	INH	
0549	01017	0 03 01637	LDA	CTRS
0550	01020	101040	ANA	=2
0551	01021	0 01 01064	SNZ	
0552	01022	140040	JMP	A3
0553	01023	54 0470	CRA	
0554	01024	0 01 01023	INA	CTRI
0555	01025	000201	JMP	*-1
0556	01026	0 02 00061	IAB	
0557	01027	0 04 01474	LDA	'61
0558	01030	0 02 00426	STA	TIM1
0559	01031	74 0570	LDA	CTRS+6
0560	01032	0 01 01031	OTA	SE11
0561	01033	000401	JMP	*-1
0562	01034	0 02 00242	ENB	
			LDA	PARS+1

0563 01035	0 06 01636	ADD	= 48	
0564 01036	0 06 01636	ADD	= 48	
0565 01037	0 04 01055	STA	*+14	
0566 01040	140442	OCT	140442	A2A
0567 01041	0 04 01047	STA	*+6	
0568 01042	140442	OCT	140442	A2A
0569 01043	0 04 01061	STA	*+14	
0570 01044	000201	IAB		
0571 01045	-0 10 00675	JST*	C12	
0572 01046	-0 10 00654	JST*	H22	
0573 01047	0 000000	DAC	**	
0574 01050	0 02 00623	LDA	ITM1	
0575 01051	-0 10 00675	JST*	C12	
0576 01052	-0 10 00670	JST*	D22	
0577 01053	0 000447	DAC	F50	
0578 01054	-0 10 00654	JST*	H22	
0579 01055	0 000000	DAC	**	
0580 01056	0 02 00622	LDA	FLG1	
0581 01057	-0 10 00675	JST*	C12	
0582 01060	-0 10 00654	JST*	H22	
0583 01061	0 000000	DAC	**	
0584 01062	140040	CRA		
0585 01063	0 04 00622	STA	FLG1	
0586 01064	000401	ENB		
0587				
0588				
0589 01065	001001	CTRI	= 4, A4, CTR2, TIM2, 8, SET2, = 51, ITM2, F	
0590 01066	0 02 00420	INH		
0591 01067	0 03 01635	LDA	CTR5	
0592 01070	101040	ANA	= 4	
0593 01071	0 01 01134	SNZ		
0594 01072	140040	JMP	A4	
0595 01073	54 0670	CRA		
0596 01074	0 01 01073	INA	CTR2	
0597 01075	000201	JMP	*-1	
0598 01076	0 02 00061	IAB		
0599 01077	0 04 01475	LDA	'61	
0600 01100	0 02 00430	STA	TIM2	
0601 01101	74 0770	LDA	CTR5+8	
0602 01102	0 01 01101	OTA	SET2	
0603 01103	000401	JMP	*-1	
0604 01104	0 02 00242	ENB		
0605 01105	0 06 01634	LDA	PAKS+1	
0606 01106	0 06 01634	ADD	= 51	
0607 01107	0 04 01125	ADD	= 51	
0608 01110	140442	STA	*+14	A2A
0609 01111	0 04 01117	OCT	140442	
0610 01112	140442	STA	*+6	A2A
0611 01113	0 04 01131	OCT	140442	
0612 01114	000201	STA	*+14	
0613 01115	-0 10 00675	IAB		
0614 01116	-0 10 00654	JST*	C12	
0615 01117	0 000000	JST*	H22	
0616 01120	0 02 00644	DAC	**	
0617 01121	-0 10 00675	LDA	ITM2	
0618 01122	-0 10 00670	JST*	C12	
0619 01123	0 000447	JST*	D22	
		DAC	F50	



0620 01124	-0 10 00654	JST*	H22	
0621 01125	0 000000	DAC	**	
0622 01126	0 02 00643	LDA	FLG2	
0623 01127	-0 10 00675	JST*	C12	
0624 01130	-0 10 00654	JST*	H22	
0625 01131	0 000000	DAC	**	
0626 01132	140040	CRA		
0627 01133	0 04 00643	STA	FLG2	
0628 01134	000401	ENB		
0629				
0630				
0631 01135	001001	CTRI	=8, A5, CTR3, TIM3, 10, SET3, =54, TIM3,	
0632 01136	0 02 00420	INH		
0633 01137	0 03 01633	LDA	CTR5	
0634 01140	101040	ANA	=8	
0635 01141	0 01 01204	SNZ		
0636 01142	140040	JMP	A5	
0637 01143	54 0270	CRA		
0638 01144	0 01 01143	INA	CTR3	
0639 01145	000201	JMP	*-1	
0640 01146	0 02 00061	IAB		
0641 01147	0 04 01476	LDA	'61	
0642 01150	0 02 00432	STA	TIM3	
0643 01151	74 0370	LDA	CTR5+10	
0644 01152	0 01 01151	OTA	SET3	
0645 01153	000401	JMP	*-1	
0646 01154	0 02 00242	ENB		
0647 01155	0 06 01632	LDA	PAR5+1	
0648 01156	0 06 01632	ADD	=54	
0649 01157	0 04 01175	ADD	=54	
0650 01160	140442	STA	*+14	
0651 01161	0 04 01167	OCT	140442	A2A
0652 01162	140442	STA	*+6	
0653 01163	0 04 01201	OCT	140442	A2A
0654 01164	000201	STA	*+14	
0655 01165	-0 10 00675	IAB		
0656 01166	-0 10 00654	JST*	C12	
0657 01167	0 000000	JST*	H22	
0658 01170	0 02 00665	DAC	**	
0659 01171	-0 10 00675	LDA	TIM3	
0660 01172	-0 10 00670	JST*	C12	
0661 01173	0 000447	JST*	D22	
0662 01174	-0 10 00654	DAC	F50	
0663 01175	0 000000	JST*	H22	
0664 01176	0 02 00664	DAC	**	
0665 01177	-0 10 00675	LDA	FLG3	
0666 01200	-0 10 00654	JST*	C12	
0667 01201	0 000000	JST*	H22	
0668 01202	140040	DAC	**	
0669 01203	0 04 00664	CRA		
0670 01204	000401	STA	FLG3	
0671		ENB		
0672				
0673				
0674				
0675				
0676 01205	0 02 00420			

\* DIGITAL OUTPUTS

DIG0	=64, A6, 11, =89, LOCF, WFDL, DCF1, DCF0
LDA	CTR5

0677	01206	0 03 01631	ANA	=64
0678	01207	101040	SNZ	
0679	01210	0 01 01244	JMP	A6
0680	01211	0 02 00433	LDA	CTRS+11
0681	01212	0 11 01630	CAS	=1
0682	01213	-0 10 01603	JST*	SPSR
0683	01214	0 01 01241	JMP	DG01
0684	01215	0 02 00242	LDA	PARS+1
0685	01216	0 06 01627	ADD	=89
0686	01217	0 06 01627	ADD	=89
0687	01220	0 04 01467	STA	LOCK
0688	01221	140040	CRA	
0689	01222	0 04 01472	STA	WRD1
0690	01223	0 35 01626	LDX	=-16
0691	01224	0 02 01472	DGR1 LDA	WRD1
0692	01225	0415 77	ALS	1
0693	01226	0 04 01472	STA	WRD1
0694	01227	-0 02 01467	LDA*	LOCK
0695	01230	101040	SNZ	
0696	01231	0 01 01235	JMP	**4
0697	01232	0 02 01472	LDA	WRD1
0698	01233	141206	AOA	
0699	01234	0 04 01472	STA	WRD1
0700	01235	0 12 01467	IRS	LOCK
0701	01236	0 12 01467	IRS	LOCK
0702	01237	0 12 00000	IRS	0
0703	01240	0 01 01224	JMP	DGR1
0704	01241	0 02 01472	DGR1 LDA	WRD1
0705	01242	74 1370	OTA	DGR1
0706	01243	0 01 01242	JMP	*-1
0707			*	
0708			*	
0709	01244		A6	
0710	01244	0 02 00420	LDA	CTRS
0711	01245	0 03 01625	ANA	=128
0712	01246	101040	SNZ	
0713	01247	0 01 01303	JMP	A7
0714	01250	0 02 00434	LDA	CTRS+12
0715	01251	0 11 01630	CAS	=1
0716	01252	-0 10 01603	JST*	SPSR
0717	01253	0 01 01300	JMP	DGR2
0718	01254	0 02 00242	LDA	PARS+1
0719	01255	0 06 01624	ADD	=105
0720	01256	0 06 01624	ADD	=105
0721	01257	0 04 01470	STA	LOCK+1
0722	01260	140040	CRA	
0723	01261	0 04 01473	STA	WRD2
0724	01262	0 35 01626	LDX	=-16
0725	01263	0 02 01473	DGR2 LDA	WRD2
0726	01264	0415 77	ALS	1
0727	01265	0 04 01473	STA	WRD2
0728	01266	-0 02 01470	LDA*	LOCK+1
0729	01267	101040	SNZ	
0730	01270	0 01 01274	JMP	**4
0731	01271	0 02 01473	LDA	WRD2
0732	01272	141206	AOA	
0733	01273	0 04 01473	STA	WRD2



0734 01274	0 12 01470	IRS	LOCK+1
0735 01275	0 12 01470	IRS	LOCK+1
0736 01276	0 12 00000	IRS	0
0737 01277	0 01 01263	JMP	DGR2
0738 01300	0 02 01473	DG02 LDA	VRD2
0739 01301	74 1270	OTA	DCOR
0740 01302	0 01 01301	JMP	*-1
0741		*	
0742		* ANALOGUE INPUTS SCAN	
0743		*	
0744		*	
0745		* BVCF =1, AX	
0746 01303		A7 BSS	0
0747 01303	0 02 00420	LDA	CTRS
0748 01304	0 03 01630	ANA	=1
0749 01305	101040	SNZ	
0750 01306	0 01 01477	JMP	AB
0751 01307	0 35 01623	LIX	=-48
0752 01310	140040	CRA	
0753 01311	-0 04 01352	STA*	AB48
0754 01312	0 12 00000	IRS	0
0755 01313	0 01 01311	JMP	*-2
0756 01314	0 02 00424	LDA	CTRS+4
0757 01315	140407	ICA	
0758 01316	0 04 01435	STA	ENS
0759 01317	0 02 00423	LDA	CTRS+3
0760 01320	0 06 01353	ADD	AB48+1
0761 01321	0 04 01354	STA	AB48+2
0762 01322	0 02 00423	LDA	CTRS+3
0763 01323	0 07 00422	SUB	CTRS+2
0764 01324	141206	ADA	
0765 01325	140407	ICA	
0766 01326	0 04 01471	STA	CHXK
0767 01327	0 35 01471	ESHL LIX	CHXK
0768 01330	0 02 00422	LDA	CTRS+2
0769 01331	0 04 01436	STA	STOP
0770 01332	0 02 01436	MUX LDA	STOP
0771 01333	74 0170	OTA	ANAG
0772 01334	0 01 01333	JMP	*-1
0773 01335	14 0070	OCF	DATA
0774 01336	140040	CRA	
0775 01337	54 0070	INA	DATA
0776 01340	0 01 01337	JMP	*-1
0777 01341	0404 72	LGR	6
0778 01342	-0 06 01354	ADD*	AB48+2
0779 01343	-0 04 01354	STA*	AB48+2
0780 01344	0 12 01436	IRS	STOP
0781 01345	0 12 00000	IRS	0
0782 01346	0 01 01332	JMP	MUX
0783 01347	0 12 01435	IRS	ENS
0784 01350	0 01 01327	JMP	ESHL
0785 01351	0 01 01437	JMP	A7A
0786 01352	1 01 1435	AB48 DAC	ABUF+48, 1
0787 01353	1 001356	DAC	ABUF+1, 1
0788 01354	000000	HSZ	1
0789 01355	000000	ABUF HSZ	48
0790 01435	000000	ENS HSZ	1

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0791 01436 000000 STUP BSZ 1
0792 *
0793 * ANALOGUE DATA PROCESSING
0794 *
0795 01437 0 02 00422 A7A LDA CTRK+2
0796 01440 0 06 01463 ADD BF
0797 01441 0 04 01464 STA ADBF
0798 01442 0 02 00242 LDA PAKS+1
0799 01443 0 06 00422 ADD CTRK+2
0800 01444 0 06 00422 ADD CTRK+2
0801 01445 0 04 01465 STA DBF
0802 01446 0 35 01471 LDX CHXK
0803 01447 -0 02 01464 REP LDA* ADBF
0804 01450 -0 10 00675 JST* C12
0805 01451 -0 10 00670 JST* D22
0806 01452 0 000000 DAC **
0807 01453 -0 10 00654 JST* H22
0808 01454 -0 001465 DAC* DBF
0809 01455 0 12 01464 IRS ADBF
0810 01456 0 12 01465 IRS DBF
0811 01457 0 12 01465 IRS DBF
0812 01460 0 12 00000 IRS 0
0813 01461 0 01 01447 JMP REP
0814 01462 0 01 01477 JMP A8
0815 01463 0 001355 BF DAC ABUF
0816 01464 000000 ADBF BSZ 1
0817 01465 000000 DBF BSZ 1
0818 01466 0 000000 RSTP DAC SKST
0819 01467 000000 LOCH HSZ 2
0820 01471 000000 CHXK HSZ 1
0821 01472 000000 WRD1 BSZ 1
0822 01473 000000 WRD2 BSZ 1
0823 01474 000000 TIM1 BSZ 1
0824 01475 000000 TIM2 BSZ 1
0825 01476 000000 TIM3 BSZ 1
0826 *
0827 * DIGITAL INPUTS
0828 *
0829 *
0830 *
0831 01477 A8 DIGI =16, A9, DGIA, =57, DGS1, DGT1
0832 01477 0 02 00420 LDA BSS 0
0833 01500 0 03 01640 ANA =16
0834 01501 101040 SNZ
0835 01502 0 01 01533 JMP A9
0836 01503 54 1170 INA DGIA
0837 01504 0 01 01503 JMP *-1
0838 01505 0 04 01602 STA HOLD
0839 01506 0 35 01626 LDX =-16
0840 01507 0 02 00242 LDA PAKS+1
0841 01510 0 06 01622 ADD =57
0842 01511 0 06 01622 ADD =57
0843 01512 0 04 01526 STA DGS1
0844 01513 140040 CRA
0845 01514 000201 IAB
0846 01515 0 02 01602 DGT1 LDA HOLD
0847 01516 0416 77 ALR 1

```

0848	01517	0 04 01602	STA	HOLD
0849	01520	101001	SSC	
0850	01521	0 01 01524	JMP	++3
0851	01522	0 02 01621	LDA	= '40300
0852	01523	0 01 01525	JMP	++2
0853	01524	140040	CRA	
0854	01525	- 0 10 00654	JST*	H22
0855	01526	0 000000	DGS1 DAC	**
0856	01527	0 12 01526	IRS	DGS1
0857	01530	0 12 01526	IRS	DGS1
0858	01531	0 12 000000	IRS	0
0859	01532	0 01 01515	JMP	DGT1
0860			*	
0861			*	
0862	01533		A9 DIGI	=32, A10, DGIH, =73, DGS2, DGT2
0863	01533	0 02 00420	BSS	0
0864	01534	0 03 01620	LDA	CTRS
0865	01535	101040	ANA	=32
0866	01536	0 01 01567	SNZ	
0867	01537	54 1070	JMP	A10
0868	01540	0 01 01537	INA	DGIB
0869	01541	0 04 01602	JMP	*-1
0870	01542	0 05 01626	STA	HOLD
0871	01543	0 02 00242	LDX	=-16
0872	01544	0 06 01617	LDA	PARS+1
0873	01545	0 06 01617	ADD	=73
0874	01546	0 04 01562	ADD	=73
0875	01547	140040	STA	DGS2
0876	01550	000201	CRA	
0877	01551	0 02 01602	IAB	
0878	01552	0416 77	DGT2 LDA	HOLD
0879	01553	0 04 01602	ALK	1
0880	01554	101001	STA	HOLD
0881	01555	0 01 01560	SSC	
0882	01556	0 02 01621	JMP	++3
0883	01557	0 01 01561	LDA	= '40300
0884	01560	140040	JMP	++2
0885	01561	- 0 10 00654	CRA	
0886	01562	0 000000	JST*	H22
0887	01563	0 12 01562	DGS2 DAC	**
0888	01564	0 12 01562	IRS	DGS2
0889	01565	0 12 000000	IRS	DGS2
0890	01566	0 01 01551	IRS	0
0891			JMP	DGT2
0892			*	
0893			*	UPDATE SCANS DONE
0894	01567	0 12 01601	*	
0895			*	
0896			*	
0897	01570	0 02 00442	REST	SIFI, SBPI
0898	01571	0 04 00034	LDA	SIFI
0899	01572	0 02 00443	STA	SIF
0900	01573	0 04 00037	LDA	SBPI
0901	01574	0 02 01600	STA	SFP
0902	01575	0 04 00204	LDA	CL06
0903			STA	GOAD
0904			*	
			*	RETN LNRA, ACLK

```

0905 01576 0 10 00027 JST LNRA
0906 01577 0 01 01000 JMP ACLK
0907 01600 004013 CL06 OCT 4013
0908 01601 000000 SCAN BSZ 1
0909 01602 000000 HOLD BSZ 1
0910 01603 0 000000 SPSK XAC MYSK
0911 01604 0 10 01606 STP JST ERCL
0912 01605 152306 BCI 1,TF

```

SCAN 100 FAST

```

0913 *
0914 * ERROR RETURN TO BASIC
0915 *

```

```

0916 01606 0 000000 ERCL DAC **
0917 01607 -0 02 01606 LDA* ERCL
0918 01610 0 04 01616 STA ** + 6
0919 01611 14 0220 OCF SCLK
0920 01612 14 0570 OCF SET1
0921 01613 14 0770 OCF SET2
0922 01614 14 0370 OCF SET3
0923 01615 -0 10 00163 JST* ERR
0924 01616 0 000000 DAC **
0925 01617 000111 FIN

```

```

01620 000040
01621 040300
01622 000071
01623 177720
01624 000151
01625 000200
01626 177760
01627 000131
01630 000001
01631 000100
01632 000066
01633 000010
01634 000063
01635 000004
01636 000060
01637 000002
01640 000020

```

```

0926 001641 BAS2 EQU *
0927 *
0928 * PATCH IN BASIC
0929 * CALLING SEQUENCE
0930 *
0931 ABS
0932 ORG '4012
0933 04012 -0 01 00716 JMP* '716
0934 ORG '716
0935 00716 0 000211 DAC CALL
0936 ORG '551
0937 00551 0 001606 DAC ERCL
0938 END

```

A1	000332	A10	001567	A2	000350	A3	001064
A4	001134	A5	001204	A6	001244	A7	001303
A7A	001437	A8	001477	A9	001533	A848	001352
ARUF	001355	ACLK	001000	ADBF	001464	ADWD	000512

ANAG	000170A	HAS1	000675	BAS2	001641	HF	001463
RSTP	001466	C	000527	C12	000675A	C21	000676A
CALL	000211	CH3	000513	CH4	000577	CHXK	001471
CIH	000073	CIHA	000117	CI1	000143	CIN1	000440
CIR	000120	CIRA	000160	CIRX	000161	CJST	000515A
CLK6	001600	CLK	000020A	CONT	000007	CTR1	000470A
CTR2	000670A	CTR3	000270A	CTRS	000420	D22	000670A
D3	000460	D4	000525	DACS	000435	DATA	000070A
DBF	001465	DGIA	001170A	DGIB	001070A	DGO1	001241
DGO2	001300	DGOA	001370A	DGOB	001270A	DGR1	001224
DGR2	001263	DGSI	001526	DGS2	001562	DGT1	001515
DGT2	001551	DISP	000164	DISG	000177	DISS	000203
FNS	001435	FRCL	001606	ERI	000370	ERR	000163
ESFL	001327	F50	000447	FAT	000441	FLG1	000622
FLG2	000643	FLG3	000664	FRST	000436	GOAD	000204
H22	000654A	HAD	001770A	HOLD	001602	I4	000526
IBUF	000230A	ICT1	000603	ICT2	000624	ICT3	000645
IFLG	000515	II4	000602	INT	000366	ITM1	000623
ITM2	000644	ITM3	000665	KT	000446	L22	000653A
LNKA	000017	LNKB	000032	LNKC	000045	LNKD	000066
LNRA	000027	LNRB	000042	LNRC	000055	LNKD	000070
LOCK	001467	M22	000674A	MASK	000162	MUX	001332
N	000461	NEXT	000437	PAKS	000241	REF	001447
SBP	000037A	SBP1	000443	SBP2	000445	SCAN	001601
SCLK	000220A	SFT1	000570A	SE12	000770A	SF13	000370A
SIP	000034A	SIP1	000442	SIP2	000444	SKST	000000
SPSR	001603	SS	004064A	STOP	000175	STP	001604
STUP	001436	SUR1	000227	SUR2	000372	SUR3	000451
SUR4	000516	TABL	000215	TIM1	001474	TIM2	001475
TIM3	001476	WRD1	001472	WRD2	001473	X	000462

0000 WARNING OR ERROR FLAGS

DAP-16 MOD 2 REV. C 01-26-71

LOW 00551  
\*START 00551  
\*HIGH 37743  
\*NAMES 12773  
\*CMN 37777  
\*JASE 37671  
\*JASF 36704  
\*ADIOS 36000  
\*FLG 36515  
\*SAT 36710  
\*ERCL 37606  
\*MYSE 37700  
\*OMOD 37710

LC



# HADIOS Exdcutive Rev.2

## Modification No.1

\* SUBROUTINE 5 3.05.78

PAGE

1

```

0001
0002
0003
0004      000653      L22      ECU      '653
0005      000676      C21      ECU      '676
0006      001370      DGOA     ECU      '1370
0007      001270      DGOB     ECU      '1270
0008
0009      000000      0 000000      SLB5     DAC      **
0010      000001      -0 10 00034      JST*     FA1
0011      000002      0000003      DEC      3
0012      000003      0000000      D5       ESZ      1
0013      000004      0000000      N5       ESZ      1
0014      000005      0000000      X5       ESZ      1
0015      000006      -0 12 00035      IRS*     FLAG
0016      000007      -0 10 00653      JST*     L22
0017      000010      -0 0000004      DAC*     N5
0018      000011      -0 10 00676      JST*     C21
0019      000012      -0 01 00033      JMP*     ERI
0020      000013      0 04 00036      STA      CH3
0021      000014      -0 10 00653      JST*     L22
0022      000015      -0 0000005      DAC*     X5
0023      000016      -0 10 00676      JST*     C21
0024      000017      -0 01 00033      JMP*     ERI
0025      000020      0415 77      ALS      1
0026      000021      000201      IAB
0027      000022      0 02 00036      LDA      CH3
0028      000023      0400 74      LRL      4
0029      000024      -0 02 00003      LDA*     D5
0030      000025      100040      SZE
0031      000026      0 01 00033      JMP      ** 5
0032      000027      000201      IAB
0033      000030      74 1370      OTA      DGOA
0034      000031      0 01 00030      JMP      *- 1
0035      000032      -0 01 00000      JMP*     SUB5
0036      000033      036370      ERI      OCT      36370
0037      000034      036710      FAT      OCT      36710
0038      000035      036515      FLAG     OCT      36515
0039      000036      000000      CH3      ESZ      1
0040
                                END

```

C21	000676A	CH3	000036	D5	000003	DGOA	001370A
DGOB	001270A	ERI	000033	FAT	000034	FLAG	000035
L22	000653A	N5	000004	SUB5	000000	X5	000005

0000 WARNING OR ERROR FLAGS  
 CAP-16 MOD 2 REV. C 01-26-71



HADIOS EXECUTIVE REV.2MOD. NO.2

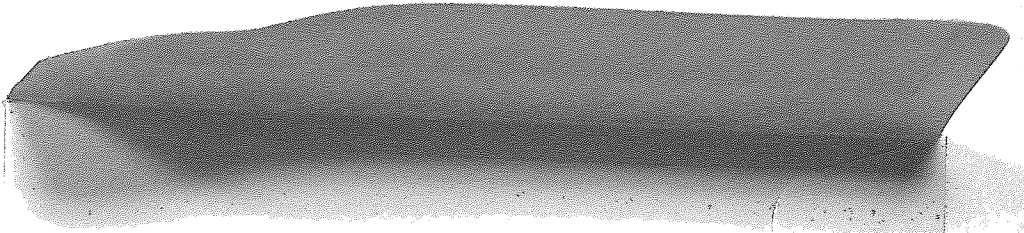
```
ABS
ORG      '37347
JMP      PCH2
ORG      '37326
JMP      PCH1
ORG      '37743
PCH1     STA      CHXR
        CRA
        STA      ENS
        LDA      '61
        STA      XREG
        LDA      '61
        STA      SAVE
        ERA      XREG
        SNZ
        JMP      *-4
        JMP      ESBL
PCH2     IRS      ENS
        LDA      '61
        ERA      SAVE
        SNZ
        JMP      DLY
        LDA      ENS
        JST*     C12
        JST*     H22
        DAC*     REP+3
        JMP      A7A
DLY      LDA      CTS
        STA      XREG
        IRS      XREG
        JMP      *-1
        JMP      ESBL
SAVE     BSZ      1
CTS      BSZ      1
XREG     BSZ      1
CHXR     EQU      '37471
ENS      EQU      '37435
C12      EQU      '675
H22      EQU      '654
REP      EQU      '37447
A7A      EQU      '37437
ESBL     EQU      '37327
END
```

A P P E N D I X E

## E.1 Listings of the Open-Loop Estimation Package (EKF3)

### The Contents of the Microfiche

Frame A1	: the contents
Frames A1,B1,.....01	: simulated open-loop estimation
A2,B2,.....02	results when the column is
A3,B3,.....03	subjected to multiple changes
A4,B4,C4	in the feed rate, composition
	and temperature. Zero mean
	White Gaussian noise is
	added to the measurements.
	Sample time is 18 seconds.



A P P E N D I X F

## F.1 Listings of the EAFF Control Package

### The Contents of the Microfiche

Frame A1 : the contents

Frames A1,B1,.....O1 : listings of the EAFF control

A2,B2,.....O2 simulation package

A3,B3,.....O3

A4,B4,C4,D4,E4

Frames E4 to F4 : the simulated column response to a single step increase in the feed rate under EAFF control. The measurements are corrupted by zero mean White Gaussian noise. Sample time is 18 seconds.

Frames F9 to G14 : the simulated column response to multiple changes in the feed rate, composition and temperature under EAFF control. The measurements are corrupted by zero mean White Gaussian noise. Sample time is 18 seconds.

Frames G14 onwards : the simulated column response to multiple step changes in the feed rate, composition and



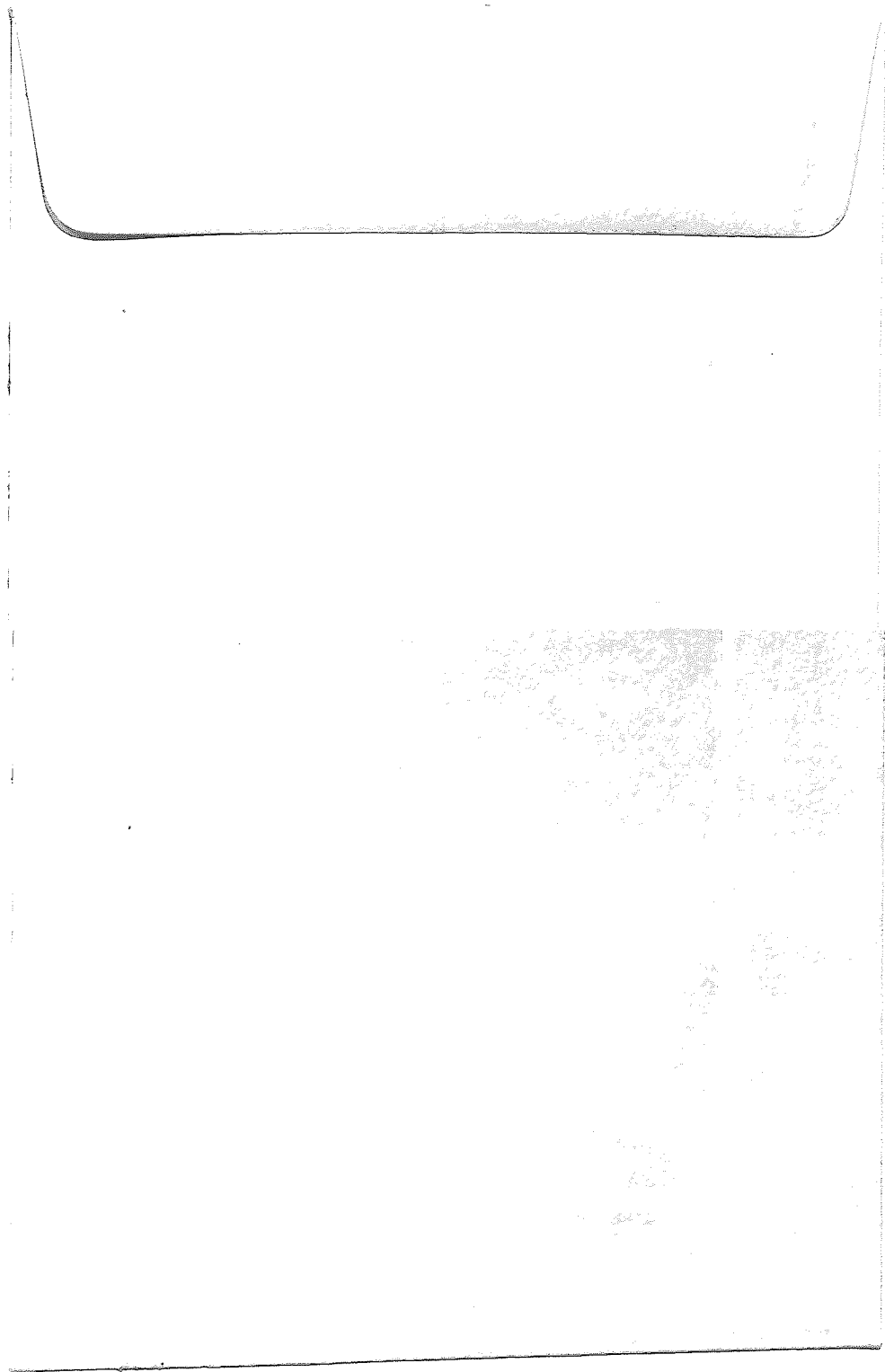
tempearture under EAFF control.

The measurements are corrupted

by zero mean White Gaussian

noise. Sample time is increased

to 25 seconds.



# APPENDIX G

The equilibrium relationship used in the model is

$$y_i = \frac{\alpha_i P_i^O(T)}{P} x_i$$

or  $y_i = K_i x_i$  ; where  $K_i = g(x_i)$

Thus this functional relationship can be included as follows:

$$f_i = \frac{L_{i-1}(x_{i-1} - x_i) + V(y_{i+1} - K_i x_i)}{M_i}$$

Thus, if we assume  $\frac{\partial K_i}{\partial x_i}$  to be negligible, the modified elements of the state transition matrix would be

$$\text{Row 1} \quad \frac{\partial f_1}{\partial x_j} = -\frac{(L_R + VK_1)}{M_1} \quad j=1 \text{ only}$$

$$\text{Rows 1 to 6} \quad \frac{\partial f_i}{\partial x_j} = -\frac{(L_{i-1} + VK_i)}{M_i} \quad i=1,6; j=i \text{ only}$$

$$\text{Row 7} \quad \frac{\partial f_7}{\partial x_j} = -\frac{(L_6 + F + VK_7)}{M_7} \quad j=7 \text{ only}$$

$$\text{Rows 8 to 10} \quad \frac{\partial f_i}{\partial x_j} = -\frac{(L_{i-1} + VK_i)}{M_i} \quad i=8,10; j=i \text{ only}$$

$$\text{Row 11} \quad \frac{\partial f_{11}}{\partial x_j} = -\frac{L_{10} + V - K_{11}V}{M_{11}} \quad j=11 \text{ only}$$

## NOTATION

### Chapter II

<u>A</u>	= relating matrix
<u>B</u>	= the matrix of left eigen vectors of <u>A</u>
B	= bottoms rate
$B_1, B_2, B_3$	= temperature measurements near the feed plate, an intermediate temperature and bottoms temperature respectively
<u>C</u>	= the matrix of right eigen vectors of <u>A</u>
$C_p$	= molar specific heat capacity
D	= distillate
<u>D</u>	= driving matrix
F	= feed rate
Z	= feed composition
$G_c$	= controller transfer function
$G_v$	= valve transfer function
$G_M$	= measurement transfer function
J	= scalar performance criterion
<u>K</u>	= proportional gain matrix
$L_n$	= liquid leaving the nth tray
<u>P</u>	= plant matrix or the Ricatti matrix
<u>Q</u>	= positive semi definite weighting matrix
<u>R</u>	= weighting matrix
R	= reflux rate
$R_I$	= internal reflux
S	= separation factor
$T_o$	= overhead temperature
$T_r$	= reflux temperature

$\underline{u}_i$  = eigen vectors of  $\underline{A}^T$   
 $\underline{u}(t)$  = control effort  
 $\underline{V}_i$  = eigen vectors of  $\underline{A}$   
 $V_n$  = vapour rate leaving the nth tray  
 $x$  = liquid composition  
 $y$  = vapour composition  
 $\underline{X}$  = vector of state variables

#### Subscripts

$m$  = measured value

#### Greek Symbols

$\lambda_i$  = eigen values of  $\underline{A}$   
 $\tau$  = hydraulic time constant

#### Filtering Notation

$A$  = continuous matrix time function  
 $D$  = continuous system input driving matrix  
 $G$  = continuous matrix time function  
 $K$  = filter gain matrix  
 $M(t)$  = continuous measurement matrix  
 $M(t_k)$  = discrete measurement matrix  
 $P$  = error covariance matrix  
 $Q$  = system noise covariance matrix  
 $R$  = measurement noise covariance matrix  
 $t$  = continuous time  
 $t_k$  = discrete time  
 $u$  = vector of deterministic system inputs  
 $v$  = vector of white Gaussian noise  
 $w$  = vector of random system disturbances represented by a zero mean white Gaussian process  
 $x$  = vector of state variables  
 $y$  = vector of measured variables

### Greek symbols

$\beta_t$	= vector of Brownian motion or Weiner process
$\Phi$	= state transition matrix
$\Gamma$	= system noise coefficient matrix
$\Gamma_D$	= discrete system input driving matrix

### Chapter III

$a, b, c, d, e$	= coefficients
$C_p$	= specific heat capacity
$M$	= mass of the liquid in the reboiler
$M_B$	= reboiler holdup
$M_D$	= reflux drum holdup
$Q$	= heat transfer rate

### Chapter IV

$A$	= Brambilla equation constant
$a$	= effective interfacial area for mass transfer
$A_a$	= active area
$B$	= Brambilla equation coefficient
$C$	= Brambilla equation coefficient
$C_p$	= specific heat capacity
$C_1, C_2, C_3$	= Antoine equation constants
$D$	= distillate rate
$D_E$	= eddy diffusivity
$d_c$	= downcomer diameter
$d_i$	= internal column diameter
$D_l$	= liquid diffusivity
$D_v$	= vapour diffusivity
$E_{mv}$	= Murphree tray efficiency



$E_v$	= vaporization efficiency
$E_{ov}$	= point efficiency
$E_{oc}$	= overall column efficiency
$E_n$	= Murphree vapour phase efficiency
$F$	= feed rate
$F_n$	= vapour flow parameter
$f_i$	= fugacity of component i
$f_i^{OL}$	= a standard state liquid fugacity
$h, H$	= liquid and vapour enthalpies respectively
$h_w$	= weir height
$h_{ow}$	= liquid height over the weir
$h_D$	= liquid height in the downcomer
$h_f$	= froth height
$h_\ell$	= pressure drop through the aerated liquid
$h_{hg}$	= hydraulic gradient across the plate
$h_{ds}$	= calculated height of clear liquid over the disperser
$K_\ell$	= liquid phase transfer coefficient
$L_n$	= liquid leaving the nth tray
$L_o$	= bottoms rate
$L_R$	= reflux rate
$M_n$	= liquid holdup on the nth tray
$M$	= molecular weight
$M_D$	= reflux drum holdup
$N_{ov}$	= number of overall mass transfer units
$N_\ell, N_v$	= liquid and vapour transfer units
$N_{pe}$	= peclet number
$N_{scg}$	= Schmidt number
$P$	= total vapour pressure on a tray
$P_c$	= total column pressure

$P_i^o(T)$	= saturation vapour pressure
$Q$	= reboiler heat duty
$q'$	= liquid flow rate
$r$	= collision diameter
$T$	= tray temperature
$t$	= time
$T_F$	= feed temperature
$T^o$	= a reference temperature
$T_r$	= reduced temperature
$T_c$	= critical temperature
$T_b$	= boiling point
$U$	= the internal energy
$U_a$	= vapour velocity through the active area
$V_n$	= vapour leaving the nth tray
$W$	= liquid flow rate or width of the flow path
$x_n$	= liquid composition on the nth tray
$y_n$	= vapour composition
$z_c$	= critical compressibility
$z_\ell$	= length of the liquid travel

#### Subscripts

$c$	= critical value
$b$	= boiling point
$m$	= mixture
$G$	= vapour phase
$i, j, n$	= refer to the ith, the jth and the nth components
$\ell$	= liquid

#### Superscripts

$L$	= liquid phase
$V$	= vapour phase

## Greek Symbols

$\gamma$	= activity coefficient
$\lambda$	= latent heat of vaporization
$\psi$	= fugacity coefficient
$\phi$	= average relative froth density on the tray
$\rho$	= density
$\mu$	= viscosity
$\theta$	= residence time of liquid in the froth zone
$\beta$	= aeration factor

## Chapter VI

The symbols are identical with the notations for filtering in Chapter II. Additionally the following notation are also used.

$\bar{x}$	= the estimated value of $x$
$\hat{x}$	= the predicted value of $x$

## Chapter VII

$I$	= the identity matrix
$x_j$	= state variables in the filters
$x_n$	= the liquid composition on a tray
$M_n$	= the liquid holdup on a tray
$M$	= measurement matrix
$\delta_i$	= the elements of the jacobian
$L_i$	= liquid rate leaving each tray
$v$	= boilup rate
$y$	= actual vapour composition in mass balances = measured variables in the filtering notation
$x_F$	= feed composition
$F$	= feed rate

LR	= reflux rate
$x_D$	= distillate composition
$x_B$	= bottom composition
R	= reflux rate = measurement noise matrix in the filtering notation
P	= the error covariance matrix
p	= total pressure
$p_i^o$	= saturation vapour pressure
$p_i$	= vapour pressure
$A_i, B_i, C_i$	= Antoine constants
T	= temperature
Q	= system noise covariance matrix

### Chapter VIII

$\hat{x}$	= estimated value of x
$\hat{x}_p$	= predicted value of x
$y$	= measurement vector
u	= control effort
$\underline{K}$	= filter gain
IAE	= integrated absolute error
LR	= reflux rate
e	= deviation from the set point
Q	= heat input rate
$x_i$	= composition

### Subscripts

s	= steady state bias
b	= bottom loop
t	= top loop

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